Optimal Control Of Two-Hop Routing In Dtns With Time-Varying Selfish Behavior

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Abstract

The transmission opportunities between nodes in Delay Tolerant Network (DTNs) are uncertain, and routing algorithms in DTNs often need nodes serving as relays for others to carry and forward messages. Due to selfishness, nodes may ask the source to pay a certain reward, and the reward may be varying with time. Moreover, the reward that the source obtains from the destination may also be varying with time. For example, the sooner the destination gets the message, the more rewards the source may obtain. The goal of this paper is to explore efficient ways for the source to maximize its total reward in such complex applications when it uses the probabilistic two-hop routing policy. We first propose a theoretical framework, which can be used to evaluate the total reward that the source can obtain. Then based on the model, we prove that the optimal forwarding policy confirms to the *threshold* form by the Pontryagin's Maximum Principle. Simulations based on both synthetic and real motion traces show the accuracy of our theoretical framework. Furthermore, we demonstrate that the performance of the optimal forwarding policy with *threshold* form is better through extensive numerical results, which conforms to the result obtained by the Maximum Principle.

Keywords: Delay tolerant network, two-hop routing, time-varying selfish behavior, optimal control

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1. Introduction

The concept of Delay Tolerant Networks (DTNs) [1] have been proposed to support many emerging networking applications, where the end-to-end connectivity cannot be assumed for technical or economical reasons, with examples including deep-space exploration [2], vehicular networks [3], mobile social networks [4], etc. Routing protocols in traditional ad hoc networks, which relay on the contemporaneous paths between communication sources and destinations, cannot work in DTNs directly.

In order to provide communication services in such highly challenging wireless networks, DTNs exploit the node mobility and opportunistic connectivity to carry and forward messages. In particular, 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].

The basic routing policy is Epidemic Routing (ER) [5], in which a message arriving at the intermediate nodes is forwarded to all neighbors. This algorithm may waste much energy and suffer from poor scalability in large networks. To overcome these problems, some lightweight policies are proposed, and the most famous one is two-hop routing algorithm [6]. In this method, only the source can forward a message to every node, and nodes other than the source can forward the message only to the destination.

It is easy to see that two-hop routing algorithm needs nodes serving as relays for the source to carry and forward message. However, this process will use certain energy, which is very precious for the wireless devices [7]. Therefore, nodes may not be willing to help the source without any reward (e.g., money) due to the impact of selfishness [8][9]. In many applications, nodes in DTNs are devices (e.g., smart phones, PDA) which can be manipulated by people [10], and people' selfish behavior is various. In fact, the buffer space or the forwarding ability can be seen as goods. The event that the source requires help from the relay nodes can be seen as that the source buys certain goods from them, so the forwarding process can be seen as the trading process of commodities, and every node wants to maximize its benefit in this process. Therefore, the relay nodes may adjust the price of their goods according to the market's state, and the selfish behavior may be varying with time. For example, if the remaining lifetime of the message is long, nodes may deem that the source may not be eager to transmit the message quickly and willing to pay too many rewards. In this case, they may help the source with only fewer rewards, that is, they are less selfish. However, if the remaining lifetime of the message is shorter, the source may be eager to transmit the message as soon as possible, so the relay nodes may ask for more rewards. The things that are used to buy the goods by the source may be virtual currency [11] or discount of other service [12]. On the other hand, the source may obtain a certain reward from the destination when the destination gets a message, and the reward may be varying with time, too. For example, the sooner the destination obtains the message, the more rewards the source may get.

In such complex applications, it may not be good for the source to request help from other nodes all the time. In particular, if the source requests help from more nodes, namely, it forwards a message to more relay nodes, the destination may obtain the message with higher speed, and the source may obtain more rewards. However, the source has to pay more rewards to these relay nodes, too. This means that the total reward that the source obtains may not be maximal. Therefore, every time the source encounters with one relay node, it may forward a message to this node only with certain probability. Different from the original two-hop routing policy, such a method can be seen as the probabilistic two-hop routing algorithm [13]-[14]. Obviously, the total reward that the source can obtain is different when the value of the probability is different. The goal of this paper is to explore efficient ways for the source to maximize its total reward in such complex applications when it uses the probabilistic two-hop routing policy.

In fact, the optimal control problem of probabilistic two-hop routing algorithm has been studied in some recent works, such as [13][14]. However, the goal of these works is only to maximize the average delivery ratio under limited energy. They fail to consider the selfish nature of nodes. For the selfish behavior, some works evaluate its impact on the routing performance [8][9]. However, none of these works considers the optimal control problem with selfish nodes.

To our best knowledge, we are the first to study the optimal control problem of two-hop routing algorithm in such complex environment. In this paper, we first propose a unifying framework through a continuous time Markov process, which can be used to evaluate the trade-off between the benefit and expenditure of the source. Then based on the framework, we formulate an optimization problem. Through Pontryagin's Maximum Principle, we explore the stochastic control problem, and prove that the optimal policy conforms to the *threshold* form in some cases. By comparing the simulation results with the theoretical results, we find 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 our model is the best among these policies.

The rest of the paper is organized as follows. Section 2 briefly introduces some works related to this paper. Section 3 first presents the theoretical framework, and then studies the optimal control problem. Simulation and numerical results are shown in Section 4. Finally, section 5 draws the conclusion.

2. Related Work

At present, many routing protocols have been proposed in DTNs. As shown in [15], existing protocols can be classified into three categories: *deterministic*, *enforced* and *opportunistic* routing. The algorithms that belong to the first category are used when contact information is known as a priori. For example, Jain et al. [16] propose a modified Dijkstra algorithm based on information about the scheduled contacts. The basic idea of the *enforced* routing is to deploy certain special prupose mobile devices, which move over predefined paths in order to provide connectivity, such as the message ferries [17] and data mules [18]. The *opportunistic* routing protocols are used when no contact informatrion is kown as a priori and no network infrastructure exists. In addition, they can be further divided into some categories. For example, the work in [15] dissects them into three classes: *message replication*, *forwarding* and *coding*. In the *message replication* scheme, a node carrying message can spawn a new copy of the message and forward it to a newly encounterd node. A classic example is ER algorithm, which belongs to the *greedy replication*. ER algorithm does not need any prior knowledge about the network, and can be used in many enviroments. Therefore, this algorithm is still a very hot topic. However, ER works in a flooding way, so its scalability and efficiency is limited in large-scale networks. A number of methods have been proposed to reduce its overhead. Among them, there are *utilized-based replication* [19], *controlled replication* [20], etc. Unlike replication, under the *forwarding* scheme, a relay node carrying a message will hand that message over a newly encountered node, such as [21]. The *coding* scheme aims to incease the delivery reliability or increase the capacity of wireless network by certain *source* or *network coding* methods [22][23]. A detail survey of the existing routing protocols in DTNs can be seen in [15].

As shown above, ER algorithm is still a hot topic with many variants. These methods have both strengths and limitations, and how to accurately evaluate the performance of these methods is very important. Some works use the simulation manner [24], but recently, theoretical manner is more popular. The work in [25] studys the performance of epidemic routing method based on the sparsely exponential graph. In addition, they explore the impact of many resources on the routing performance, such as buffer space, the number of copies, etc. Then the performance of ER algorithm in DTNs with heterogeneous nodes is explored in [26]. The authors in [27] get the generic theoretical upper bounds for the information propagation speed in large-scale mobile and intermittently connected network, and then [28] explores the information propagation speed in bidirectional vehicular delay tolerant network. The work in [29] studys the performance of two-hop relay routing under limited packet lifetime. The authors in [30] study the ER routing performance with contention. From these theoretical models, we can see that many factors can have certain impact on the ER algorithm. For example, if there are more copies, the performance will be better. However, to make more copies, more energy has to be used [13][14]. Therefore, there are some works which begin to consider the optimal control problem. These works 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 [13] studies the optimal control problem of probabilistic two-hop routing algorithm, and they prove that the optimal forwarding policy conforms to the *threshold* form. Then the work in [14] explores the problem again with continuous time Markov process.

However, none of above works considers the selfish nature of nodes which is common in the real word. Panagakis et al. explore the impact of selfishness through simulation [31]. There are also some works which study the impact of nodes' selfishness by theoretical method, such as [32]-[33]. For example, the work in [32] proposes a Markov model to evaluate the impact of selfishness, and [33] presents a unifying framework to analyse the exact distribution of relevant performance metircs, different from previous works which studies the expected value. Li et al. [34] are the first to propose the concept of *social selfishness* in DTNs and present a user-centered routing method which is adaptive to the selfish nature. The behavior of *social selfishness* means that people are more willing to help their friends. Then some works explore the impact of *social selfishness* through Markov model when the network has two communities [35][36]. Nearly all of these works find that the selfish behavior can make the routing performance be worse. However, to our best knowledge, there is no work which explores the optimal control problem in DTNs when nodes are selfish.

3. Theoretical Framework and Optimal Control

3.1 Network Model

We assume that the network has N relay nodes, and one of them is the source S. Moreover, there is one destination D. Therefore, the network totally has N+1 nodes. At time 0, the source S creates a message denoted by MS. To make the destination get the message quickly, S adopts the two-hop routing policy, that is, it requests help from the relay nodes. Due to the selfish nature, S has to pay a certain reward. For simplicity, we assume that if S requests help from node j at time t, the reward that it pays to j is $PR(t)$. In addition, if the destination D gets the message at time *t*, *S* can obtain a certain reward from *D* denoted by *RR*(t).

Because *S* has to pay a certain reward once it requires help from other nodes, it may not do this every time it encounters with a relay node. We assume that *S* requests help at time *t* with probability *p*(*t*) (forwarding probability), and *p*(*t*) belongs to [0, 1]. Different from the original two-hop algorithm, routing policy in such case can be seen as probabilistic two-hop routing policy. Once *S* encounters with one relay node and *S* is willing to pay the requested reward, the relay node will obtain the message. In this paper, we assume that relay nodes that are carrying a message must be willing to forward toward *D* when they encounter with *D*.

Nodes in the network can communicate with each other only when they come into the transmission range of each other, which means a communication contact, so the mobility rule of nodes is critical. In this paper, we assume that the occurrence of contacts between two nodes follows a Poisson distribution. This assumption has been used in wireless communications for many years. At present, some works show that this assumption is only an approximation to the message transmission process, and they reveal that nodes encounter with each other according to the power law distribution [37]. However, they also find that if you consider long traces, the tail of the distribution is exponential. In addition, [38] 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 Poisson process and validate their model experimentally on real motion traces [39]-[40]. According to these descriptions, the exponential inter-meeting time is rational in some applications, and we assume that the inter-meeting time between two nodes follows an exponential distribution with parameter β. Simulations based on real motion traces show that our theoretical model based on such assumption is very accurate.

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
β	Exponential parameter of the inter-meeting time
T	The maximal lifetime of the message
$PR(t)$	The reward that the relay node requires at time t
$RR(t)$	The reward that the source obtains if D gets mesage at t
$p(t)$	Forwarding probability at time t
$X(t)$	The number of relay nodes carrying message at time t
$F(t)$	The delivery ratio at time t
$U(t)$	The total income that the source obtains till time t

3.2 Theoretical Framework

Let $X(t)$ denote the number of relay nodes (include *S*) that are carrying the message (denoted by *MS*) at time *t*. Because only the source *S* has the message at time 0, we have $X(0)=1$. In this paper, we assume that nodes carrying a message do not receive the same message any more. Given a time interval Δt, we can obtain,

$$X(t+\Delta t)=X(t)+\sum_{j\in\{Y(t)\}}\varphi_j(t,t+\Delta t) \tag{1}$$

Symbol $\{Y(t)\}$ denotes the set of relay nodes without the message at time *t*, and the cardinality of this set is N-$X(t)$. $\varphi_j(t, t+\Delta t)$ denotes the event that whether node j gets the message MS in time interval $[t, t+\Delta t]$. If $\varphi_j(t, t+\Delta t)=1$, node j gets the message, but if $\varphi_j(t, t+\Delta t)=0$, it does not get the message. Note that the event happens only when node j encounters with S and S is willing to require help from node j. As shown above, two nodes encounter with each other according to an exponential distribution with parameter β. Node j encounters with a specific node (e.g., S) in interval $[t, t+\Delta t]$ with probability $1\text{-}e^{-\beta\Delta t}$. Because S requires help at time t with probability $p(t)$, we can see that S forwards the message to j with probability $p(t)(1\text{-}e^{-\beta\Delta t})$. That is, we have,

$$p(\varphi_j(t,t+\Delta t)=1)=p(t)(1-e^{-\beta\Delta t}) \tag{2}$$

Based on Eq.(1) and Eq.(2), we can obtain,

$$\begin{aligned} &E(X(t+\Delta t))=E(X(t))+(N-E(X(t)))E(\varphi_j(t,t+\Delta t)) \\ &\Rightarrow E(\dot{X}(t))=\beta(N-E(X(t)))p(t) \end{aligned} \tag{3}$$

Note that $E(X(t))$ denotes the expectation of $X(t)$. 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. Let $F(t)$ denote the delivery ratio when the given time is t. Before getting its value, we first give another symbol $H(t)=1\text{-}F(t)$, which denotes the probability that D does not obtain the message before time t. Moreover, let $H(t, t+\Delta t)$ denote the probability that D does not obtain the message in interval $[t, t+\Delta t]$. Therefore, we have,

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

There are $X(t)$ relay nodes which may forward the message to the destination D at time t, so we can obtain the following equation easily.

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

Further, we can obtain,

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

Let $U(t)$ denote the total reward that the source obtains till time t. We can obtain:

$$\begin{aligned} U(t+\Delta t)&=U(t)+\eta_D(t,t+\Delta t)RR(t+\mu) \\ &\quad -\sum\nolimits_{j\in\{Y(t)\}} PR(t+\rho_j)\varphi_j(t,t+\Delta t) \end{aligned} \tag{7}$$

In time interval $[t, t+\Delta t]$, once a relay node (e.g., j) gets the message (e.g, at time $t+\rho_j$), S must pay a certain reward denoted by $PR(t+\rho_j)$, $0\le\rho_j\le\Delta t$. In addition, once D gets the message in interval $[t, t+\Delta t]$, (e.g, at time $t+\mu$), S will obtain the reward denoted by $RR(t+\mu)$, $0\le\mu\le\Delta t$. Symbol $\eta_D(t,t+\Delta t)$ denotes whether D gets the message in interval $[t, t+\Delta t]$. If $\eta_D(t,t+\Delta t)=1$, node D gets the message, but if $\eta_D(t,t+\Delta t)=0$, it does not get the message. Note that this event means that D is not carrying the message before. Therefore, we have,

$$\begin{aligned} p(\eta_D(t,t+\Delta t)=1)&=H(t)(1-H(t,t+\Delta t)) \\ &=F(t+\Delta t)-F(t) \end{aligned} \tag{8}$$

Based on Eq. (7) and Eq. (8), we have,

$$\lim_{\Delta t\to 0}\frac{E(U(t+\Delta t)-U(t))}{\Delta t}=RR(t)\lim_{\Delta t\to 0}\frac{E(F(t+\Delta t)-F(t))}{\Delta t} -PR(t)\lim_{\Delta t\to 0}\frac{\sum_{j\in\{Y(t)\}}\varphi_j(t,t+\Delta t)}{\Delta t} \quad (9)$$

$$\Rightarrow E(\dot{U}(t))=RR(t)\,E(\dot{F}(t))-PR(t)\,E(\dot{X}(t))$$

3.3 Optimal Control

Based on Eq.(9), we can obtain,

$$E(U(T))=\int_0^T(RR(t)E(\dot{F}(t))-PR(t)E(\dot{X}(t)))dt \quad (10)$$

Our main goal is to maximize the value of $E(U(T))$, which is a function about the forwarding probability $p(t)$, and T can be seen as the maximal lifetime of the message.

Let $((X, F), p)$ be an optimal solution. In particular, at time t, X denotes the value of $E(X(t))$ and F denotes the value of $E(F(t))$. Similarly, p denotes the value of $p(t)$, which means that the source S forwards the message to relay nodes with probability $p(t)$ at time t. Consider the *Hamiltonian* H, and *co-state* or *adjoint* functions λ_X and λ_F defined as follows:

$$\begin{aligned} H &= RR\dot{F}-PR\dot{X}+\lambda_F\dot{F}+\lambda_X\dot{X} \\ &=(RR+\lambda_F)\dot{F}+(\lambda_X-PR)\dot{X} \\ &=\beta(RR+\lambda_F)(1-F)X+\beta(\lambda_X-PR)(N-X)p \end{aligned} \quad (11)$$

$$\begin{cases}\dot{\lambda}_F=-\dfrac{\partial H}{\partial F}=\beta X(RR+\lambda_F)\\ \dot{\lambda}_X=-\dfrac{\partial H}{\partial X}=-\beta(RR+\lambda_F)(1-F)+(\lambda_X-PR)\beta p\end{cases} \quad (12)$$

Note that at time t, RR and PR are simple expressions of $RR(t)$ and $PR(t)$, separately.

The *transversality* conditions are shown as follows:

$$\lambda_F(T)=\lambda_X(T)=0 \quad (13)$$

Then according to Pontryagin's Maximum Principle ([41]), there exist continuous or piece-wise continuously differentiable state and co-state functions X, F, p, which satisfy:

$$p\in\arg\max_{0\le p^*\le 1}H(\lambda_F,\lambda_X,(F,X),p^*) \quad (14)$$

This equation between the optimal control parameter p and the *Hamiltonian* H allows us to express p as a function of the state (F, X) and *co-state* (λ_F, λ_X), resulting in a system of differential equations involving only the state and *co-state* functions, rather than the control function. In fact, this equation means that maximizing the value of $E(U(T))$ equals to maximizing the corresponding *Hamiltonian*. In particular, at certain time t, the state (F, X) and *co-state* (λ_F, λ_X) can be seen as constants, and $p(t)$ can maximize H at this time. Therefore, according to Eq.(11), we can obtain the optimal forwarding policy as follows:

$$p=\begin{cases}1, \lambda_X>PR \text{ and } X<N\\ 0, \lambda_X<PR \text{ and } X<N\end{cases} \quad (15)$$

The number of relay nodes is N, so if X=N, every node is carrying the message, and the source S cannot forward to any node, so p can be any value. If X<N, we have N-X>0, and if

$\lambda_X > PR$, we can obtain $(N\text{-}X)(\lambda_X\text{-}PR)>0$. Therefore, H is increasing with p, and we can obtain the optimal value of the forwarding probability easily, that is, p=1. The optimal forwarding probability can be obtained easily in other cases in similar way, and we have Eq.(15). In the rest of this paper, we only consider the case $X<N$, that is, at least one relay node is not carrying the message.

Below, we will prove that when the functions of $PR(t)$ and $RR(t)$ satisfy certain conditions, the optimal policy has a simple structure. The conditions are: $PR(t)$ is monotone increasing with time t, but $RR(t)$ is a decreasing function; $PR(t)$ and $RR(t)$ are continuous and differentiable; they are non-negative. In fact, the maximal lifetime (T) of the message is fixed, so if the value of t is bigger, the remaining lifetime (T-t) is shorter. In this case, the relay nodes may think that the source may be eager to transmit the message to D quickly, so they may ask for more rewards. That is to say, if the value of t is bigger, the value of $PR(t)$ may be bigger. Therefore, the condition that $RR(t)$ is increasing is rational in some environments. On the other hand, it is better if the destination gets the message earlier, so the assumption that $RR(t)$ is a decreasing function is rational in certain applications, too.

If above conditions can be satisfied, the optimal policy conforms to the *threshold* form and has at most one jump. In particular, we have the following Theorem.

Theorem 1: If $PR(t)$ and $RR(t)$ satisfy above conditions, the optimal forwarding policy satisfies: $p(h)$=1, $h<s$ and $p(h)$=0, $h>s$, $0\le s\le T$.

Proof: First, note that both the functions $RR(t)$ and $PR(t)$ are positive, and this means that if the source requests help from other nodes, it must pay a certain reward to these nodes. On the other hand, if D gets the message, S can get certain benefit.

Similar to the work in [42], we define a new function as follows,

$$f = \lambda_X - PR \tag{16}$$

Then, we can obtain,

$$\dot{f} = \dot{\lambda}_X - \dot{PR} \tag{17}$$

From Eq.(12), we have,

$$\dot{\lambda}_X = -\frac{\partial H}{\partial X} = -\beta(RR + \lambda_F)(1-F) + f\beta p \tag{18}$$

Therefore, when $f(s)$=0, we have,

$$\begin{aligned}\dot{f}(s) &= \dot{\lambda}_X(s) - \dot{PR}(s) = -\beta(RR(s)+\lambda_F(s))(1-F(s)) + f(s)\beta p(s) - \dot{PR}(s) \\ &= -\beta(RR(s)+\lambda_F(s))(1-F(s)) - \dot{PR}(s)\end{aligned} \tag{19}$$

Because we have $RR + \lambda_F \ge 0$ (See Theorem 2), and PR is an increasing function, we can get $\dot{f}(s) < 0$. That is, if $f(s) = 0$, the function will decrease at time s.

Then we assume that $f(s)<0$. According to Eq.(15), we have $p(s)$=0. Combing with Eq.(17) and Eq.(18), we can also get Eq.(19). Furthermore, we can know that f will decrease at time s.

In summary, if $f(s)\le 0$, f will decrease at time s. Therefore, if $f(s)\le 0$, we have $f(h)<0$, $h>s$. What's more, according to Eq.(15), the optimal policy satisfies: $p(h)$=1, $h<s$, and $p(h)$=0, $h>s$. That is, once $p(s)\ne 1$, it will be 0 later and then remain unchanged all the time, so the optimal policy conforms to the *threshold* form and has at most one jump. This proves that Theorem 1 is correct.

Theorem 2: If $PR(t)$ and $RR(t)$ satisfy above conditions, we have $RR + \lambda_F \geq 0$.

Proof: Based on Eq.(13), we know $\lambda_F(T)=0$, so λ_F cannot be bigger than 0 at any time. Otherwise, we assume that λ_F is bigger than 0 at certain time (say, s), and then we have $\beta X(RR+\lambda_F)>0$. From Eq.(12), we can see that λ_F is increasing at time s, so λ_F will be even bigger, that is, we have $\lambda_F(h)>0$, $h>s$. This means that $\lambda_F(T)>0$ and this is contradiction with Eq.(13), so λ_F cannot be bigger than 0.

Further, because $\lambda_F(T)=0$, $\dot{\lambda}_F$ cannot be smaller than 0 at any time. Otherwise, we assume that $\dot{\lambda}_F$ is smaller than 0 at certain time (say, s), and then we have $RR + \lambda_F < 0$ from Eq.(12). Therefore, λ_F is decreasing at time s. Because $RR(t)$ is a decreasing function, based on Eq.(12), we know that $RR + \lambda_F$ is decreasing at time s, and this means that $\dot{\lambda}_F$ is still negative, so we have $\dot{\lambda}_F(h) < 0, h > s$. Because we have proved $\lambda_F \leq 0$, we can easily obtain $\lambda_F(h) < 0, h > s$. This means that $\lambda_F(T) < 0$ and this is contradiction with Eq.(13), so we have $\dot{\lambda}_F \geq 0$, and we can further get $RR + \lambda_F \geq 0$ from Eq(12).

4. Simulation and Numerical Results

4.1 Simulation Results

In this section, we will check the accuracy of our theoretical model, and we run several simulations using the Opportunistic Network Environment (ONE) [43]. The first simulation is based on the famous Random Waypoint (RWP) mobility model [44], which is commonly used in many mobile wireless networks. We assume that there are 600 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 communication range is 10m. The second simulation is based on a real motion trace from about 2100 taxis for nearly one month in Shanghai city collected by GPS [45], in which the reports are recorded every 40 seconds within the area of 102 km^2. The reports include: the taxis' ID, the longitude and latitude coordinates of the current location, the speed, etc. In addition, we assume that two taxis can communicate with each other if their distance is shorter than 50m. We randomly pick 600 nodes from this trace, with other settings the same as that in RWP model.

The functions of $RR(t)$ and $PR(t)$ may be any form. For simplicity, we define: $RR(t)=1000e^{-t/10000}$ and $PR(t)=10(1- e^{-t/10000})$. For the forwarding policy, there may be many different settings, too. Our main goal in this section is to check the accuracy of our theoretical framework, so we only consider two special cases. Case 1: $p(t)=1$, $t\geq0$; Case 2: $p(t)=0$, $t\geq0$. The first case means that the source requests help every time it encounters with one relay node, but the second case means that it never requests help from relay nodes. At the beginning of each simulation, one message is generated with maximal lifetime T, and the source and destination are randomly selected among these nodes. Each simulation is repeated 20 times. Let the value of T increase from 0s to 20000s, we can obtain **Fig. 1** and **Fig. 2**, separately.

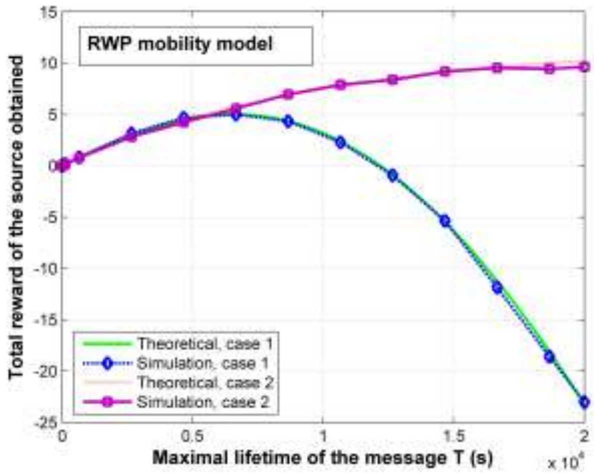

Fig. 1. Simulation and numerical results comparisio with RWP mobility model

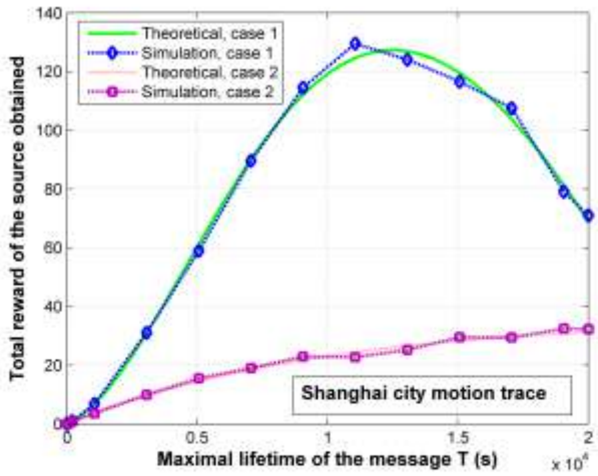

Fig. 2. Simulation and numerical results comparisio with Shanghai city motion trace

From **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 2.63% for the RWP mobility model, and 4.56% for the Shanghai city motion trace. This demonstrates the accuracy of our theoretical framework. For this reason, we can use the numerical results obtained by our theoretical framework to evaluate the performance of the optimal forwarding policy. In addition, the results in **Fig. 1** and **Fig. 2** also show that the performance will be different when the forwarding probability is different. In particular, the source may obtain a negative reward if it requests help all the time. Moreover, the total reward may be bigger if the source never forwards the message to other relay nodes in some cases (see **Fig. 1**).

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 evaluate the performance of the optimal forwarding policy, which is the *threshold* form. For comparison, we consider other 3 cases: Case 1: $p(t)=1$, $t\geq 0$; Case 2: $p(t)=0$, $t\geq 0$; Case 3: *random*, that is, the value of $p(t)$ is randomly selected from the interval [0, 1]. Let the maximal lifetime of the message be 50000s and other settings are the same as that in simulation, and then we can obtain Fig. 3. The result presents the total reward that the source obtains at any time t, which belongs to [0, 50000].

The result in Fig. 3 shows that the optimal forwarding policy is the best one among the policies in the figure, and this conforms to the result obtained by the Pontryagin's Maximum Principle. With the optimal forwarding policy, the source can always get the maximal total reward. This further shows that our optimal control policy is correct. Therefore, though the source can increase the average delivery ratio by requesting help with bigger probability, it will pay more reward, while its total reward may be less. In fact, the average delivery ratio in the optimal forwarding policy is lower than that in Case 1, and the result is shown in Fig. 4. This means that we cannot maximize the total reward through maximizing the average delivery ratio. Therefore, the objective function in [13][14] is not proper in this paper. In other words, when the relay nodes are selfish, the source does not require help from others at certain time, and this may decrease the average delivery ratio. However, this behavior also decreases its expenditure, so the total reward may be bigger.

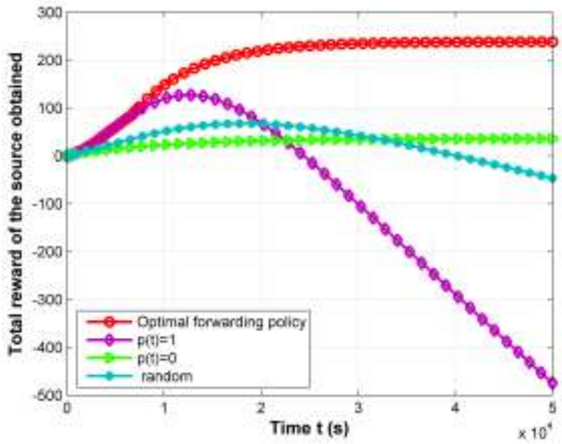

Fig. 3. Performance under different forwarding policies

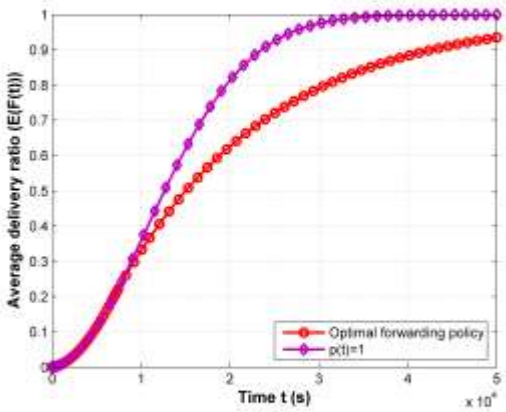

Fig. 4. Average delivery ratio under different forwarding policies

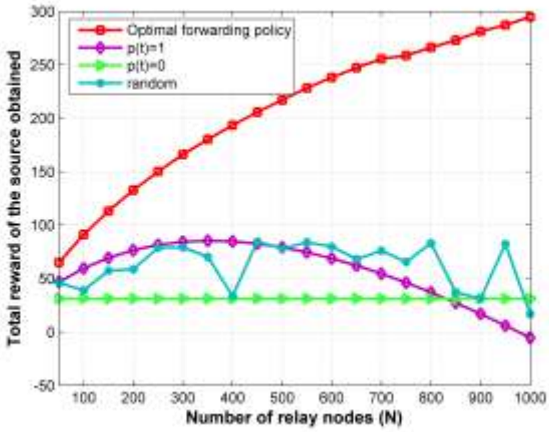

Fig. 5. Performance when the number of relay nodes is different

Now, we make a further comparison about the performance of different forwarding policies when the number of relay nodes is different. In this case, we assume that the maximal message lifetime equals to 20000s, and let the number of relay nodes increase from 50 to 1000. Other settings remain unchanged. Numerical result is shown in Fig. 5. This result also demonstrates that the optimal forwarding policy is better than other policies in the figure. In addition, the total reward under the optimal forwarding policy is increasing with the number of relay nodes. In fact, when there are more relay nodes, the source can request help from more nodes at early time. Because the reward that the relay nodes request is increasing with time, this will decrease the cost of the source and the source may stop forwarding at early time. As shown above (see Eq.(15)), the source will stop requesting help at certain time (say, s). In particular, if the time s satisfies: $E(X(s))=N$ or $\lambda_X(s)=PR(s)$, the source will stop forwarding the message to any relay node after time s. As shown in **Fig. 6**, the value of s is decreasing with time, and this means that the source really stops forwarding earlier when the network has more relay nodes. Therefore, this result conforms to Theorem 1.

In above simulation and numerical results, we define: $RR(t)=1000e^{-t/10000}$ and $PR(t)=10(1-e^{-t/10000})$. However, there may be many different forms for both functions. Here, we study another special case, that is, we define: $RR(t)=1000(t+1)^{-\rho}$ and $PR(t)= (t+1)^{\rho}$, $\rho\geq 0$. Then we mainly consider 4 forwarding policies: Case 1: optimal forwarding policy; Case 2: $p(t)=1$, $t\geq 0$; Case 3: $p(t)=0$, $t\geq 0$; Case 4: *random*. Let the maximal lifetime of the message be 50000s and other settings are the same as that in simulation, and then we can obtain **Fig. 7** and **Fig. 8** respectively when the value of ρ equals to 0.1 and 0.01, separately.

The results in both figures show that the optimal forwarding policy is better. Moreover, these results show that the total reward of the source obtains will be distinct when the functions $RR(t)$ and $PR(t)$ are different, even though the source uses the same forwarding policy. For example, when the source uses the optimal forwarding policy, the reward that it gets is about 300 at 30000s if $\rho=0.1$, but the reward is about 810 if $\rho=0.01$. In addition, when $\rho=0.01$, the deviation between the optimal forwarding policy and Case 2 is very small. For example, there nearly no deviation between them when the time is increasing from 0s to 30000s, and the biggest deviation is only about 8.8% which appears at 50000s (see **Fig. 8**). However, when $\rho=0.1$, the deviation is much bigger. For example, the deviation is about (312.9958-123.8098)/123.8098=152.8% at 50000s (see **Fig. 7**), which is much bigger than 8.8%.

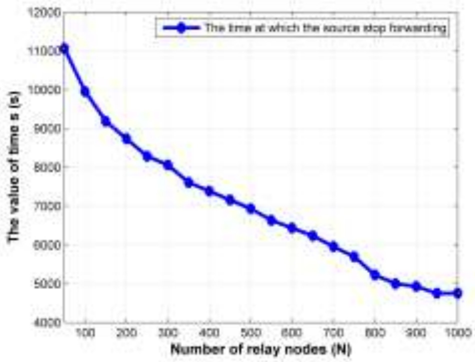

Fig. 6. The time when the source stop forwarding under the optimal forwarding policy

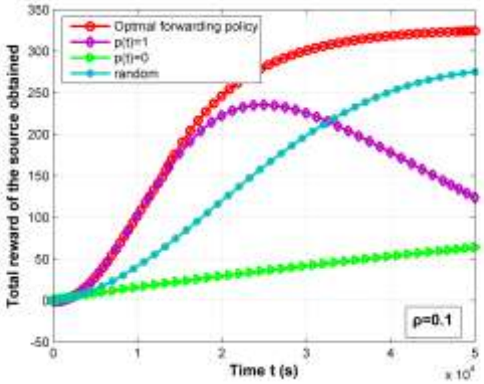

Fig. 7. Performance when the value of ρ equals to 0.1

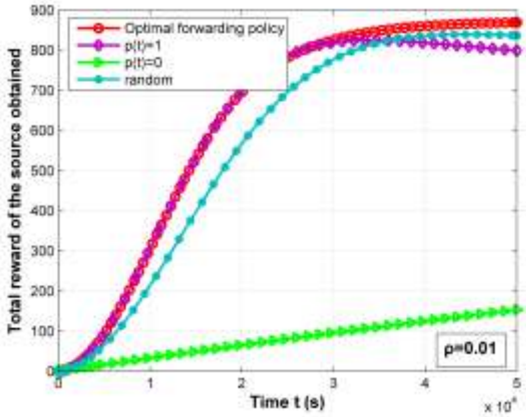

Fig. 8. Performance when the value of ρ equals to 0.01

5. Conclusion

Because the communication opportunity is rare in DTNs, the source often requests help from other nodes. Due to the impact of selfishness, nodes may ask for a certain reward (denoted by $PR(t)$) from the source, and the reward may be varying with time. For example, when the message stays in the network for a long time, the relay nodes may think that its remaining lifetime is shorter, so they may ask for more rewards from the source. Moreover, the source can obtain a certain reward (denoted by $RR(t)$) from the destination when the destination gets the message, and such reward may be varying, too. For example, the sooner the destination obtains the message, the more rewards the source may get. In this paper, we propose a unifying framework to evaluate the total reward that the source gets under different forwarding probability when it uses the probabilistic two-hop routing algorithm. Then based on the framework, we study the optimal control problem. In particular, we prove that the optimal forwarding policy conforms to the *threshold* form when $PR(t)$ is a monotone increasing function and $RR(t)$ is a monotone decreasing function. Simulations based on both synthetic and real motion traces show the accuracy of our theoretical framework. Numerical results show that the optimal forwarding policy obtained by Eq.(15) is the better.

In this paper, we assume that $PR(t)$ is a monotone increasing function and $RR(t)$ is a monotone decreasing function. However, there are also many other cases. For example, because the message stays in the network for a long time, the relay nodes may also think that there are many replicas of the message in the network, and the source may be unwilling to request help any more. That is to say, if the message stays in the network for a long time, the relay nodes may ask for less reward. Our theoretical framework can be applied to evaluate the total reward in these cases, too. In the future, we will attempt to explore the optimal control problem in these cases.

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