Energy Efficient Beaconing Control Strategy Based on Time-Continuous Markov Model in DTNs

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***Abstract*—In delay tolerant networks (DTNs), unpredictable mobility leads to the uncertainty of network topology, and it is hard to maintain an end-to-end connection from the source to the destination. To realize the forwarding of the messages, beaconing is used to detect the contact probabilities. However, beaconing frequency not only influences the detection probability of the available communications, but also concerns the energy consumption rate. The higher the beaconing frequency is, the faster the energy is consumed. The energy consumption leads to the reduction of the network survival time, due to the lack of energy supply. In contrast, the lower the beaconing frequency is, the less frequently available communications are detected, which also leads to a decrease in delivery rate. Therefore, it is meaningful to find out the most suitable beaconing frequency in specific DTNs. In this paper, we propose an energy efficient Dynamic Beaconing Control strategy in Energy-Constrained DTNs (DBCEC) based on the time-continuous Markov model. Six different dynamic function forms are respectively used to control the beaconing frequency. Simulations based on the synthetic mobility pattern and real mobility traces are conducted in ONE, and the results show that DBCEC-E achieves a better delivery rate without affecting the average delay and the overhead ratio, compared with other beaconing control strategies.**

***Index Terms*—DTNs, Energy-constrained, Markov, Beaconing.**

I. Introduction

Delay-tolerant networks (DTNs) [2], are a type of challenged network in which end-to-end transmission latency may be arbitrarily long due to occasionally connected links. A traditional TCP/IP protocol is no longer available in DTNs, due to the lack of an end-to-end path between the source and the destination. Therefore, a bundle layer, including the storage-carry-forward paradigm and custody-transfer thought, is inserted between the transport layer and application layer. The typical application scenarios of DTNs include interplanetary networks [3], military field networks [4], disaster response networks [5], rural countryside networks [6], wildlife tracking networks [7], and pocket-switched networks [8, 9], etc.

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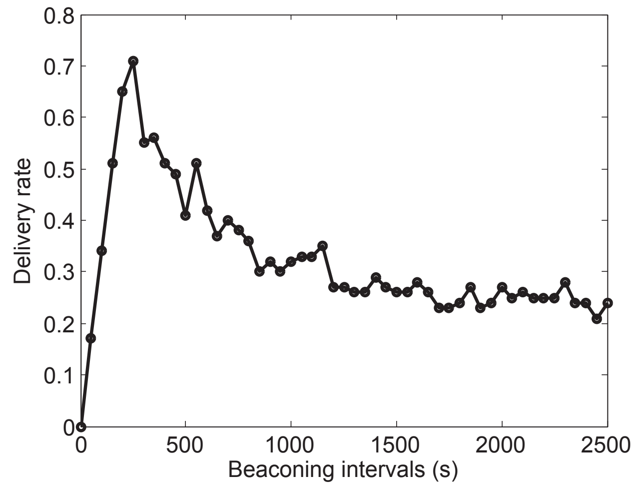


Fig. 1. The relationship between delivery rate and beaconing intervals in energy-constrained DTNs. When the beaconing interval is very low, the energy will be consumed quickly. When beaconing interval is very high, plenty of communication opportunities will be missed.

The store-carry-forward paradigm requires the node in DTNs to keep a bundle until the next reliable hop is determined, unless the time-to-live (TTL) of the bundle expires. Successful delivery occurs only when one or more infected nodes, which are the custodies of some messages, encounter the destination. Therefore, it is critical to choose a suitable next-hop [10] to forward the messages in the store-carry-forward paradigm. An enormous amount of research in terms of routing protocol in DTNs assumes that two nodes within the communication range of each other can exchange the messages; however, how the node can get the information of whether there are other nodes in its communication range is commonly not mentioned. In other words, the detection method of available communications is not reasonably explained. The most important thing is that the detection of contacts is bound to consume energy. Therefore, the effective utilization of energy in DTNs [11, 12] is also crucial, while commonly neglected. For example, in Underwater Wireless Sensor Networks [13] and Disaster Response Networks, the vehicles could not be timely charged. In this paper, we argue that beaconing signal and transmission operations are both necessary to improve the delivery rate. However, frequent beaconing operations and a mass of message transmissions inevitably result in rapid energy consumption, and shorten the node's lifetime. Subsequently, the connectivity of the whole network is undermined and the message delivery rate is bound to decrease. Therefore, it is actually difficult to directly apply the existing scheduling policies and routing protocols in an energy-constrained DTNs, especially in wildlife tracking networks and PSNs, where the nodes' energy cannot be supplied in a timely manner.

According to the above analyses, there is a lack of a beaconing control strategy that maximizes the delivery rate utilizing the limited energy constraint. It is obvious that the consumption of energy resources in DTNs mainly includes two aspects: *beaconing energy* for contact detection, and *communication energy* for message transmission. Note that the nodes commonly stay in the beaconing state for most of their lifetimes and wait to detect an available communication opportunity. The nodes enter the transmission state only when the proper next-hop node is within the communication range. Therefore, the beaconing frequency not only influences the beaconing energy consumption, but also concerns the communication energy consumption. To optimize the network performance, we propose a dynamic and self-adapting beaconing control strategy, which can avoid the following two drawbacks: (1) Because the beaconing frequency is too high, the nodes consume excessive energy. (2) Because the beaconing frequency is too low, the nodes miss plenty of communication opportunities.

Actually, we believe that there is always a similar relationship as shown in Fig. 1 between delivery rate and beaconing intervals in the energy-constrained DTNs. When the beaconing interval is short, the nodes are able to detect more communication opportunities, while also consuming more beaconing energy. In contrast, when the beaconing interval is long, the nodes could miss more communication opportunities, while also saving more beaconing energy. Therefore, the delivery rate first increases along with the increase of the beaconing interval. However, the excessively long beaconing interval also results in the waste of communication opportunities, and causes the decrease of the delivery rate. In conclusion, it is really important to trade off the beaconing frequency in order to maximize the delivery rate; with this in mind, the optimal beaconing control strategy becomes finding out the peak point in Fig. 1. To solve the above problem, we propose a dynamic beaconing control strategy DBCEC for Epidemic routing by using an optimal function to control the beaconing frequency.

The main contributions are summarized as follows:

- We propose a Dynamic Beaconing Control strategy in Energy-Constrained DTNs (DBCEC) based on the time-continuous Markov model, in order to optimize the delivery rate utilizing the limited beaconing energy.
- According to the enhancement of DBCEC, we achieve the six dynamic beaconing strategies: DBCEC-C, DBCEC-L, DBCEC-E, DBCEC-I, DBCEC-R, and DBCEC-S by using a constant function, a linear decline function, an exponential decay function, a linear increment function, a raised function, and a sunk function to respectively control the beaconing frequency.
- We conduct extensive simulations on both the synthetic random-waypoint mobility pattern and real mobility trace. The results show that the DBCEC has a high degree of accuracy in terms of estimating the optimal beaconing interval, and DBCEC-E significantly improves delivery rate, compared with the other dynamic beaconing control strategies.

The remainder of the paper is organized as follows. We review the related work in Section 2. In Section 3, we describe the system model and point out the assumptions in terms of the network environment. Based on the system model and the assumptions, the Dynamic Beaconing Control strategy in Energy-Constrained DTNs (DBCEC) based on the time-continuous Markov model is proposed in Section 4. In Section 5, we evaluate the performance of DBCEC through extensive simulations. We conclude the paper in the last section.

II. RELATED WORK

A. Routing Protocol in DTNs

In the past few years, a mass of routing protocols and forwarding algorithms have been proposed to improve the delivery rate or average delay in DTNs.

The previous work focusing on the routing algorithm in DTNs can be generally classified into the following two categories: the copy-based routing protocol and the utility-based routing protocol. The main thought of copy-based routing methods is to improve the delivery ratio by increasing the number of redundant copies. According to whether the number of messages are limited, the copy-based routing methods can also be classified into fixing quotas and flooding. The classic routing method with the fixed quotas is Spray and Wait [14], and the typical routing method based on flooding is Epidemic [15]. The utility-based routing methods make routing decisions according to link state, mobile model, context information, flow distribution, and so on. The typical routing methods are MobySpace [16] and MEED [17].

However, all the above optimal forwarding algorithms do not consider the energy optimization problem. In other words, the above routing protocols assume that the energy consumptions in terms of the communication and beaconing can be supplied timely, which is not practical in some real DTN environments.

B. Energy Optimization in DTNs

Recently, an enormous amount of research has been devoted to the energy optimization in DTNs, and some achievements have been obtained in terms of saving the communication and beaconing energy.

For example, Eitan Altman proposes an ideal control strategy regarding node activation and message transmission in [18], and properly deals with the following two problems: when to activate the node and what the beaconing frequency is. However, they define the states of the nodes as falling into the three different categories, so they could not achieve a unified beaconing control strategy. Uddin $et\ al.$ in [19] propose a multi-copy routing protocol to maximize the delivery rate and reduce the average delay by efficiently utilizing the remaining energy. Subsequently, in the same research group, Tarek Abdelzaher $et\ al.$ in [20] propose a multi-copy interactional routing protocol for energy-constrained disaster networks and ensure that the routing protocol is still able to achieve a better delivery rate when energy is extremely limited. Panayiotis Kolios $et\ al.$ in [21] present a routing protocol and a scheduling strategy to maximize the utilization rate of energy and analyze the trade-off between energy efficiency and average delay in detail. Yong Li $et\ al.$ study the energy issues in [22] and [23]. In [22], they propose an ideal opportunistic forwarding strategy to minimize energy consumption and achieve the strategy both in static and dynamic perspectives. In [23], in order to maximize the delivery rate in energy-constrained DTNs, an energy control method is also proposed. Shengbo Yang in [24] presents a contact detection method according to the social properties and cooperation relationships between nodes in pocket switched networks (PSNs), which can ensure an excellent delivery rate when energy is limited. To minimize the communication energy consumption for disaster response networks, where energy cannot be timely supplied.

In this paper, in order to optimize the delivery rate, we propose a dynamic beaconing control strategy DBCEC based on the time-continuous Markov model. The strategy trades off the delivery rate and the energy consumption through controlling the beaconing frequency. Next, six different function forms are used for controlling beaconing frequency, and we further obtain the six dynamic beaconing control strategies respectively.

III. SYSTEM MODEL

We consider the following delay tolerant network environment in this paper. N mobile nodes exist in the network. When a new message is generated, it randomly selects two nodes as the source and the destination, respectively. The messages will be generated when the system is initialized. The initial time-to-live for a message is denoted by TTL. A message disappears from the network when the TTL becomes zero. Besides, the local buffer size and transmission rate are sufficient to store and forward all the messages. In other words, messages can be successfully transmitted as long as the contacts are successfully detected. We use the Epidemic [15] routing protocol to forward the messages. Due to the reason that messages are forwarded by all possible contact opportunities in Epidemic routing protocol, it can achieve the best performance in the delivery rate and average delay as long as the network resources (energy, buffer size, $et\ al.$) are sufficient.

However, when the network is energy-constrained, how to reasonably control the beaconing frequency becomes a hot potato. If the beaconing frequency is too low, some contacts are bound to be missed, which leads to a decrease in the delivery rate. If we increase the beaconing frequency, excessive energy will be consumed, which also results in the reduction of the network lifetime. To solve the above problems, we propose a dynamic beaconing control strategy DBCEC for Epidemic routing. Then we present DBCEC-C, DBCEC-L, DBCEC-E, DBCEC-I, DBCEC-R, and DBCEC-S by using a constant function, a linear decline function, an exponential decay function, a linear increment function, a raised function, and a sunk function to respectively control the beaconing frequency. Simulation results show that DBCEC-E can significantly improve the delivery rate without affecting the average delay and overhead ratio, compared with other beaconing control strategies. In this paper, we also make the following assumptions regarding the network environment. No node has an immunization strategy or a mechanism to send acknowledgments to confirm the receipt of the messages. Nodes move independently of each other under the popular mobility patterns, such as random walk, random waypoint, and random directions. The inter-meeting times between nodes tail off exponentially [25, 26].

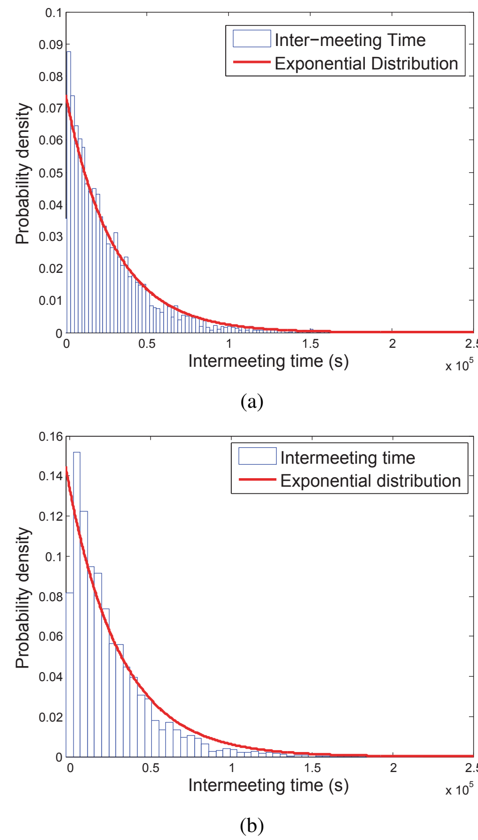


Fig. 2. Inter-meeting time distributions for the random-waypoint mobility pattern (a) and the epfl data set (b).

In DTNs, messages are forwarded through mutual contacts. Therefore, the inter-meeting times between nodes in a pair will influence the delivery rate significantly. We define the inter-meeting time as follows: inter-meeting time is the time elapsed from the end of the previous contact to the start of the next contact.

The recent research shows that inter-meeting times satisfy exponential distribution under many popular scenarios such as random walk, random waypoint, and random direction. Our simulation is based on a random waypoint mobility pattern. Therefore, we first plot the distribution of inter-meeting times in Fig. 2 through the simulation, and then match it to an exponential distribution. As illustrated in Fig. 2, we see that the inter-meeting times appropriately follow an exponential distribution: $f(x) = \lambda e^{-\lambda x}\quad$ (x>0) in practice. Assume that λ is the parameter for the exponential distribution of inter-

TABLE I
MAIN NOTATION USED THROUGHOUT THE PAPER

Symbol	Meaning
N	Total number of the nodes in the network
M	Total number of the distinct messages in the network
TTL	Initial time-to-live for messages
R	Remaining time-to-live for messages
t	Elapsed time for the messages since they are generated
$m(t)$	Number of the nodes with the message after t
$F(t)$	Beaconing frequency after the elapsed time t
E	Average inter-meeting time between nodes in a pair
λ	The parameter in the distribution of inter-meeting times
α	Energy consumption of each time of transmission
β	Energy consumption of each time of beaconing
Ω	Maximum energy constraint to deliver a message
$P_c(t)$	Probability that node pair can communicate at time t
$P(t)$	Delivery rate of the messages at time t

meeting times, and E denotes the mathematical expectation value; then $\lambda = \frac{1}{E}$. Main notations used in this paper are illustrated in Table I.

IV. DYNAMIC BEACONING CONTROL STRATEGY

A. Energy Consumption Constraint

First of all, we consider the following problem: how to calculate $P_c(t)$, the description of $P_c(t)$ is shown in Table I. Since the inter-meeting times follow an exponential distribution (with parameter λ), the probability that nodes in a pair can contact each other at any time is λ. In addition, nodes in a pair can communicate with each other at time t as long as the following two conditions are satisfied: (1) Nodes in a pair can contact each other at time t. (2) Nodes in a pair can detect the contact through beaconing at time t. Therefore, $P_c(t)$ can be expressed as Eq. (1).

$$P_c(t) = F(t)\lambda \tag{1}$$

Next, we consider a simple case in which only one distinct message exists in the network. The message randomly selects the source node, which begins to disseminate the message in DTNs at the initial time of the system. In consideration of the assumptions in Section 3, all the analyses and conclusions should be extendable with suitable bookkeeping when there is more than one distinct message. In order to analyze the dissemination process of the message in the Epidemic routing protocol, $m(t)$ is defined as the number of nodes holding a copy of the message after elapsed time t and $m(0) = 1$. We use S to denote the set of $m(t)$, then $S = \{m(t) \mid 0 \leq t \leq TTL\} = \{1, 2, 3, 4...N\}$, where N is the total number of nodes in the network and t is the system time. Assume that there are equally spaced $t_0 - t_{n+1}$ satisfying: $0 \leq t_0 < t_1 < \cdots < t_{n+1} \leq TTL$. Therefore, it is not difficult to find that Eq. (2) can be derived.

$$\begin{aligned} &P\{m(t_{n+1}) = i_{n+1} | m(t_k) = i_k; 0 \leq k \leq n\} \\ &\quad = P\{m(t_{n+1}) = i_{n+1} | m(t_n) = i_n\} \end{aligned} \tag{2}$$

According to Eq. (2), we find that the next state of $m(t)$ only depends on the current state rather than the sequence of states that precedes the current state. With this in mind, the sequence of $m(t)$ is obviously a time-continuous Markov chain. Therefore, we can use the Markov model to predict the change trend of $m(t)$ along with the system time t.

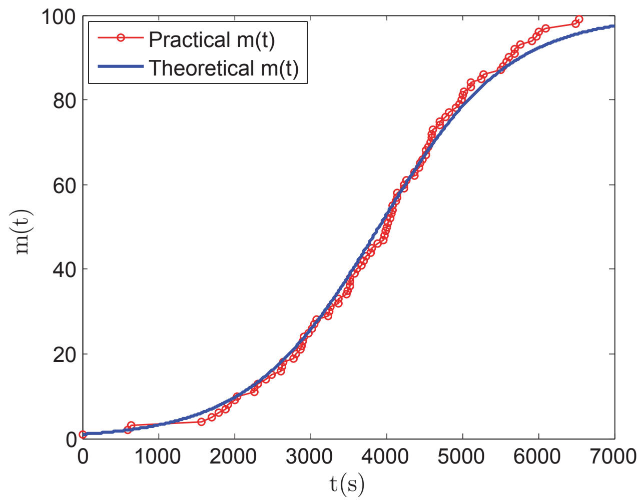


Fig. 3. The theoretical value and practical value of $m(t)$.

Next, in order to obtain the value of $m(t)$, the derivative of $m(t)$ is considered. At system time t, there are $m(t)$ nodes holding the message, and the remaining $N - m(t)$ nodes have not seen the message. The increment of $m(t)$ depends on the number of the nodes among remaining $N - m(t)$ nodes that will be infected by the message within the next short period. Moreover, the probability that the nodes in a pair can contact and communicate with each other is $P_c(t)$. At the same time, there are $(N - m(t))m(t)$ node pairs whose contacts can lead to the increment of $m(t)$. Therefore, Eq. (3) is achieved to calculate the derivative of $m(t)$. By combining Eq. (1) and Eq. (3) and $m(0) = 1$, $m(t)$ can be solved and expressed as Eq. (4).

$$\frac{\mathrm{d}m(t)}{\mathrm{d}t} = P_c(t)(N - m(t))m(t) \tag{3}$$

$$m(t) = \frac{N}{(N-1)e^{-N\lambda \int_0^t F(t)\mathrm{d}t} + 1} \tag{4}$$

To further verify the accuracy of $m(t)$ predicated by the Markov model, we conduct the simulation of random-waypoint mobility pattern to observe the changing curve of $m(t)$, which is plotted as the practical results and is compared with the theoretical results (i.e., the result calculated through Eq. (4)) as shown in Fig. 3, which shows that the theoretical results of $m(t)$ predicted by the Markov model can closely match the practical results. The above phenomenon indicates that Eq. (4) can be used to calculate $m(t)$ precisely. In addition, it is not difficult to find that there are $m(t)$ nodes holding the message among the total N nodes. Therefore, the delivery rate at time t can be expressed as the ratio between the number of nodes holding the message and the total number of nodes in the network. Therefore, Eq. (5) is achieved.

$$P(t)=\frac{m(t)}{N}=\frac{1}{(N-1)e^{-N\lambda\int_0^t F(t)\mathrm{d}t}+1} \quad (5)$$

Note that the energy consumption of each message transmission and beaconing are α and β, respectively. In addition, the number of the nodes with the message at time t is $m(t)$, which leads to the result that the energy consumption of message transmission is $\alpha(m(t)-1)$. Similarly, for the reason that the beaconing frequency at the elapsed time t is $F(t)$, the energy consumption of beaconing for each node is $\beta\int_0^t F(t)$. The total beaconing energy consumption is $\beta N\int_0^t F(t)$. Moreover, the maximum energy constraint to deliver a message is Ω. Therefore, the system energy constraint at time t can be expressed as Eq. (6).

$$\alpha(m(t)-1)+\beta N\int_0^t F(t)\mathrm{d}t\le\Omega \quad (6)$$

Next, we discuss the following problem: how to determine the beaconing frequency within the limited energy constraint so that we can get the maximum delivery rate. Considering that the initial time-to-live for messages is TTL, the optimization objective is to maximize the $P(TTL)$, which is the delivery rate before the deadline, and the constraint condition turns out to be as follows:

$$\alpha(m(TTL)-1)+\beta N\int_0^{TTL} F(t)\mathrm{d}t\le\Omega \quad (7)$$

Therefore, the above problem can be expressed as the following optimization problem:

$$\begin{aligned}&Maximize\ \ P(TTL)\\ &s.t.\quad \alpha(m(TTL)-1)+\beta N\int_0^{TTL} F(t)\mathrm{d}t\le\Omega\end{aligned} \quad (8)$$

B. Beaconing Frequency in Constant Function

Theorem 1: Eq. (8) is satisfied only when Eq. (9) is satisfied.

$Proof$: We prove theorem 1 by a contradiction. According to Eq. (5), we can get the following equation: $P(TTL)=\frac{1}{(N-1)e^{-N\lambda\int_0^{TTL}F(t)\mathrm{d}t}+1}$. It is not difficult to find that $P(TTL)$ increases along with the increase of $\int_0^{TTL}F(t)\mathrm{d}t$. In addition, we consider that the energy constraint is shown as follows: $\alpha(m(TTL)-1)+\beta N\int_0^{TTL}F(t)\mathrm{d}t\le\Omega$, where we can find that $\alpha(m(TTL)-1)$ and $\beta N\int_0^{TTL}F(t)\mathrm{d}t$ also increase along with the increase of $\int_0^{TTL}F(t)\mathrm{d}t$. Assume that there is $F(t)$ satisfying $\alpha(m(TTL)-1)+\beta N\int_0^{TTL}F(t)\mathrm{d}t=\Omega_1\le\Omega$, which can maximize the optimization objective. However, there must be $F'(t)$ satisfying Eq. (8) and $\int_0^{TTL}F'(t)\mathrm{d}t\ge\int_0^{TTL}F(t)\mathrm{d}t$. Therefore, $P'(TTL)\ge P(TTL)$, which proves that $F(t)$ is not the best solution to Eq. (8). Therefore, in order to maximize the delivery rate, Eq. (9) as a function of $\int_0^{TTL}F(t)\mathrm{d}t$ must be satisfied. Theorem 1 is proved.

$$\alpha(m(TTL)-1)+\beta N\int_0^{TTL} F(t)\mathrm{d}t=\Omega \quad (9)$$

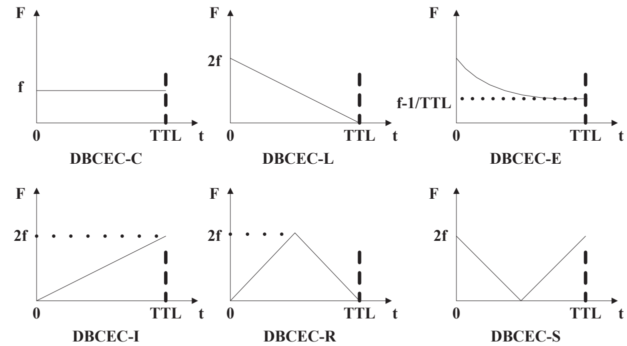


Fig. 4. Six different dynamic beaconing control strategies.

By solving Eq. (9) with the help of Matlab software, we achieve the approximate solution of $\int_0^{TTL}F(t)\mathrm{d}t$ as shown in Eq. (10), where lambertw(c) is the solution of $xe^x=c$ (x is the variable and c is the constant).

$$\int_0^{TTL}F(t)\mathrm{d}t=\frac{(-\beta\cdot\text{lambertw}(\frac{1}{N-1}\lambda\frac{\alpha}{\beta}e^{\frac{(\Omega+\alpha)\lambda}{\beta}})+(\Omega+\alpha)\lambda)}{\lambda\beta N} \quad (10)$$

In conclusion, when the beaconing frequency satisfies E-q. (10), the delivery rate of the whole network is optimized. However, there are a myriad of function forms in terms of $F(t)$ satisfying Eq. (10). It is really a challenging problem to find the optimal $F(t)$ to maximize the $P(TTL)$. In other words, for the reason that $F(t)$ affects the rate of energy consumption, finding an optimal $F(t)$ to maximize the delivery rate becomes the most important problem to be addressed in this paper.

In the analysis, we can find that the number of nodes holding the message in the local buffer shows an increasing trend, and the available contact opportunities of these nodes show a decreasing trend. In order to fully study the impact on the delivery rate of different beaconing control strategies, we define $F(t)$ as a constant function (DBCEC-C), a linear decline function (DBCEC-L), an exponential decay function (DBCEC-E), a linear increment function (DBCEC-I), a raised function (DBCEC-R), and a sunk function (DBCEC-S), respectively. The curve shapes of the above functions are shown in Fig. 4. We elaborate on the details in terms of the six beaconing control strategies in the remainder of this section, and observe the merits and demerits of the six beaconing strategies by conducting simulations in Section 5.

First of all, $F(t)$ is defined as a constant function, i.e., $F(t)=f$. According to Eq. (10), we can achieve the optimal beaconing frequency as shown in Eq. (11), and we refer to as DBCEC-C.

$$f=\frac{(-\beta\cdot\text{lambertw}(\frac{1}{N-1}\lambda\frac{\alpha}{\beta}e^{\frac{(\Omega+\alpha)\lambda}{\beta}})+(\Omega+\alpha)\lambda)}{TTL\cdot\lambda\beta N} \quad (11)$$

According to Eq. (11), it is not difficult to find that that the optimal beaconing frequency is related to three parameters: the number of nodes, the inter-meeting time, and the TTL of messages. However, the inter-meeting time is determined by the node density in the fixed network area, and therefore, the optimal beaconing frequency is actually decided by the node density and TTL of messages. Furthermore, the optimal beaconing frequency is obviously an inverse proportional function of both node density and message TTL. In the analysis, the reason is shown as follows: in energy-constrained DTNs, the larger node density means a lower energy constraint for each node: we need to reduce the beaconing frequency to save energy, in order to maximize the delivery rate. A larger TTL of messages also indicates a longer survival time, we also need to reduce the beaconing frequency, in order to prolong the survival time. As a result, the lower beaconing frequency actually achieves the optimal solution, which closely matches the theoretical results.

C. Beaconing Frequency in Dynamic Function

Next, we consider the following situation: $F(t)$ is defined as a linear decline function, i.e., $F(t) = a_l t + b_l$, where a_l is a negative constant, and b_l is a positive constant. In the beaconing control strategy of a linear decline function, we attempt to reduce the beaconing frequency from a high value to zero along with the increase of system time t. With this in mind, combining Eq. (10), $F(t) = a_l t + b_l$ and $F(TTL) = 0$, we respectively get the values of a_l and b_l as shown in Eq. (12) and Eq. (13), and successfully obtain the dynamic beaconing control strategy in a linear decline function form, which is referred to as DBCEC-L.

$$a_l = \frac{-2f}{TTL} \tag{12}$$

$$b_l = 2f \tag{13}$$

Similarly, $F(t)$ is defined as a linear increment function, i.e., $F(t) = a_i t$, where a_i is a positive constant. We seek to increase the beaconing frequency from zero to a high value along with the increase of system time t. Therefore, combining Eq. (10), $F(t) = a_i t$ and $F(0) = 0$, we successfully obtain the value of a_i as shown in Eq. (14). The dynamic beaconing control strategy called DBCEC-I in a linear increment function form is achieved.

$$a_i = \frac{2f}{TTL} \tag{14}$$

Next, a raised function and a sunk function as shown in Fig. 4 are respectively used to control the change of $F(t)$ along with the increase of system time t. First of all, $F(t)$ is denoted as a raised function, which gradually rises, and then gradually decreases with the increase of time t, i.e., $F(t) = a_r t, t < TTL/2$, and $F(t) = -a_r t + b_r, t \geq TTL/2$, where a_r and b_r are both positive constants. And then, combining Eq. (10) and $F(TTL) = 0$, we respectively get the values of a_r and b_r as shown in Eq. (15) and Eq. (16), and successfully obtain the dynamic beaconing control strategy in a raised function form, which is referred to as DBCEC-R.

$$a_r = \frac{4f}{TTL} \tag{15}$$

$$b_r = 4f \tag{16}$$

Similarly, when $F(t)$ is denoted as a sunk function, i.e., $F(t) = -a_s t + b_s, t < TTL/2$, and $F(t) = a_s t - b_s, t \geq TTL/2$, where a_s and b_s are both positive constants. We omit the derivation details for the beaconing control strategy in a sunk function form and show the calculation results of a_s and b_s in Eq. (17) and Eq. (18), respectively. We refer to the control strategy as DBCEC-S.

$$a_s = \frac{4f}{TTL} \tag{17}$$

$$b_s = 2f \tag{18}$$

Lastly, we consider that $F(t)$ is defined as an exponential decay function, i.e., $F(t) = \lambda e^{-\lambda t} + d$. We also note that $\int_0^{TTL} F(t)\mathrm{d}t = \int_0^{TTL} \lambda e^{-\lambda t} + d\mathrm{d}t = 1 - e^{-\lambda TTL} + d \cdot TTL$. According to Eq. (10), we can get the approximate solution of d as shown in Eq. (19) and obtain the dynamic beaconing control strategy DBCEC-E.

$$d = f - \frac{1}{TTL} \tag{19}$$

Simulation results show that, compared to other beaconing control strategies, DBCEC-E achieves the best delivery rate without affecting average delay and overhead ratio. At the beginning, there is only one source in the network, and a higher beaconing frequency could help spread out the message. And then, reducing the beaconing frequency could help to save energy and prolong the live time. However, if the beaconing frequency reduces to 0 before TTL, they will miss some transmission opportunities before the deadline. Therefore, DBCEC-E could achieve a better delivery rate than that of DBCEC-L.

V. PERFORMANCE EVALUATION

Having presented our system model and elaborated on the six different dynamic beaconing control strategies in energy-constrained DTNs, in this section, we conduct simulations based on both the synthetic random-waypoint mobility pattern and the real mobility traces. Subsequently, we report our findings through analyzing the simulation results.

A. Evaluation Settings

In order to verify the accuracy of the dynamic beaconing control strategy in energy-constrained DTNs (DBCEC) and compare the performances of the six different beaconing control strategies (i.e., DBCEC-C, DBCEC-L, DBCEC-E, DBCEC-I, DBCEC-R, and DBCEC-S), we use the Opportunistic Network Environment (ONE) simulator [27] to conduct extensive simulations under the following two situations: (1) Random-waypoint: a synthetic mobility pattern in which each node chooses its destination randomly and walks along the shortest path to the destination, and then repeats the above behavior. (2) Epfl data set [28]: it contains GPS data from 500 San Francisco taxis acquired over 30 days, without loss of generality; we use the data of the first 200 taxis in this paper and plug the epfl data set into ONE.

TABLE II
SIMULATION PARAMETERS UNDER RANDOM-WAYPOINT SCENARIO

Parameter	Value
Simulation time	2500s, 5000s, 10000s
Simulation area	4500m×3400m
Number of nodes	100
Moving speed	2m/s
Transmission speed	250kBps
Transmission range	100m
Buffer size	500M
TTL	2500s, 5000s, 10000s
Message size	250kB
Transmission consumption	1J
Beaconing consumption	5J
Energy constraint for each node	50J, 100J, 150J, 200J

First of all, to evaluate the performance of proposed beaconing control strategy under a random-waypoint mobility pattern, we configure the random-waypoint simulation environment as follows: 100 distinct messages are generated when the system is initialized, after which messages are no longer generated; Messages are forwarded according to the Epidemic routing protocol. In considering that the message TTL and initial energy can both affect the performance of beaconing control strategy according to Eq. (11), the simulation times and message TTLs in the random-waypoint mobility pattern are set to 2500s, 5000s, and 10000s, respectively, and the simulation times and message TTLs in the Epfl data set are set to 2500s, 5000s, and 7500s. The initial energy of each node in random-waypoint scenario (i.e., the energy constraint) are set to 50J, 100J, 150J, and 200J, and the initial energy in Epfl is set to 100J, 200J, 300J. Other parameters are given in Table II and III. The simulations can be divided into the following three parts: the first part is to verify the accuracy of Eq. (11) in DBCEC under random-waypoint mobility pattern; the second part is to compare the performances of the six different dynamic beaconing control strategies; the last part is to verify the accuracy of Eq. (11) under the Epfl data set.

While a range of data is gathered from the simulations, we take the following four main performance metrics into consideration.

(1) Delivery rate is the ratio between the number of messages successfully delivered to the destination and the total number of messages generated in the network.

(2) Average delay is the average time elapsed for the successful delivery of the messages.

(3) Overhead ratio (load ratio) is the ratio between the result of the successfully forwarded message number minus the successfully delivered message number, and the successfully delivered message number.

(4) Survival time is the time elapsed from the time that system is initialized to the time that all nodes' energy has run out.

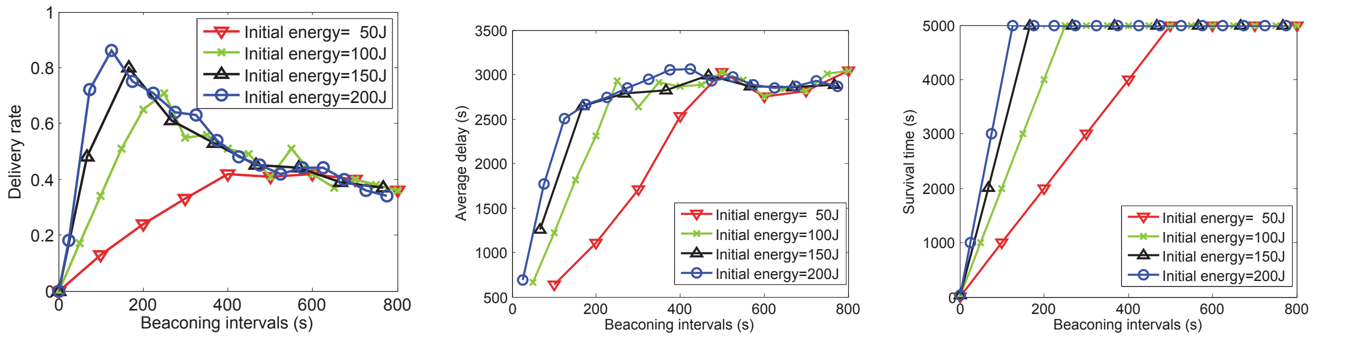
B. Simulation Analysis Under Random-Waypoint Mobility Pattern

We set the mobility pattern to random-waypoint in ONE simulator and set the number of nodes to 100 by default in a fixed area of 4500m×3400m. In order to analyze the impact caused by the energy constraint, the transmission speed and buffer size are assumed to be sufficient. In the simulation environment as described before, we observe the performances (delivery rate, average delay, and survival time) of DBCEC-C through changing the beaconing intervals from 1s to 800s.

First of all, the energy constraint for each node is set to 50J, 100J, 150J, and 200J, respectively. According to Eq. (11), we work out the corresponding optimal beaconing frequencies as follows: $\frac{1}{500}$, $\frac{1}{250}$, $\frac{1}{167}$, $\frac{1}{125}$, i.e., the optimal beaconing intervals should be 500s, 250s, 167s, 125s, respectively. In order to verify the veracity of DBCEC, simulations are done to evaluate the performance of DBCEC-C in different beaconing intervals. The delivery rate, average delay, and survival time are plotted in Fig. 5.

Fig. 5-(a) shows the changes in delivery rate over the beaconing intervals from 1s to 800s. As a result, the delivery rate first increases and then decreases along with the increase of the beaconing interval under different initial energy. Most of all, the practical beaconing interval corresponding to the peak point in Fig. 5-(a) closely matches the theoretical value of the beaconing interval calculated through Eq. (11). For example, when the initial energy is 200J, the theoretical value of the beaconing interval calculated through Eq. (11) is 125s, and we can observe the simulation results from Fig. 5-(a), which shows that the delivery rate first increases along with the increase of beaconing interval from 1s to 125s, and then decreases with the increase of beaconing interval from 125s to 800s. Therefore, we can make a conclusion that beaconing control strategy DBCEC-C does a good job in terms of estimating the optimal beaconing frequency. In other words, beaconing frequency calculated by Eq. (11) can maximize delivery rate under random-waypoint mobility pattern. Moreover, we can find that when beaconing interval is less than the optimal value, excessive energy is consumed due to the high beaconing frequency. Therefore, the survival time of the network is not long enough to support message delivery, which leads to a decrease of the delivery rate. However, when the beaconing interval is larger than the optimal value, some contacts cannot be detected, which also results in the low delivery rate. In the analysis, the practical results match the theoretical results, the dynamic beaconing control strategy in energy-constrained DTNs (DBCEC) actually achieves a better delivery rate.

Fig. 5-(b) describes the variation trend of average delay as a function of beaconing intervals. We can observe the simulation results in which the beaconing interval increases, and the average delay also increases, which is shown in Fig. 5-(b). This is reasonable and natural for the reason that the larger beaconing interval results in fewer communication opportunities. Therefore, it will take a longer period of time for delivery to be completed from the source to the destination, which further increases the average delay in the network. It is worth noticing that the amplitude of variation of the average delay has an obvious turning point. For example, when the initial energy is 200J, the average delay mushrooms along with the increase of beaconing interval from 1s to 125s, and then slowly increases along with the beaconing interval from 125s to 800s. The turning point is precisely the optimal beaconing interval, which indicates that the calculation result of Eq. (11)



(a) Delivery rate (b) Average delay (c) Survival time

Fig. 5. Delivery rate, Average delay, and Survival time as a function of beaconing intervals with different initial energy under random-waypoint scenario.

not only optimizes the delivery rate, but also improves the average delay to some extent.

Fig. 5-(c) provides some important data in terms of the survival time performance. It shows that as the beaconing interval increases, survival time of the whole network increases linearly. It is mainly due to that the beaconing energy consumption occupies a major portion of the total energy consumption, and the beaconing control strategy has a direct impact on the survival time. However, when the beaconing interval reaches the optimal value calculated by Eq. (11), the survival time no longer increases. Therefore, we can make a conclusion that the optimal beaconing interval can also maximize the survival time, which further verifies the accuracy of DBCEC-C.

Secondly, the initial energy for each node is set to 100J, and the time-to-live (TTL) for each message is set to 2500s, 5000s, and 10000s, respectively. According to Eq. (11), we approximately work out the corresponding optimal beaconing frequencies: $\frac{1}{125}$, $\frac{1}{250}$, and $\frac{1}{500}$, i.e., the optimal beaconing intervals should be 125s, 250s, and 500s, respectively. In order to further verify the veracity of DBCEC, simulations are done to evaluate the performance of DBCEC-C in different beaconing intervals. Similarly, the performances in terms of delivery rate, average delay and survival time are also plotted in Fig. 6.

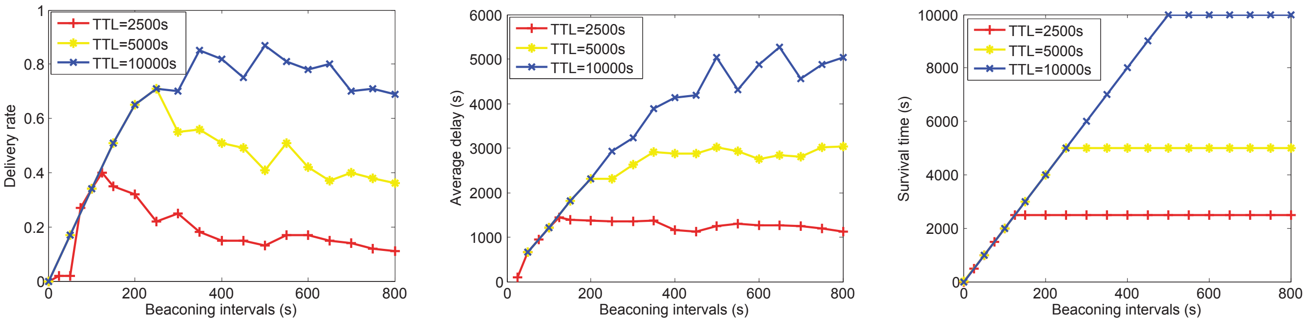
Fig. 6-(a) shows the changes in delivery rate over the beaconing intervals from 1s to 800s with different message TTLs. As can be seen, similar to before, the delivery rate first gradually rises, and then gradually decreases along with the increase of the beaconing interval under different message TTLs. Similarly, the practical beaconing interval corresponding to the peak point in Fig. 6-(a) closely matches the theoretical value of beaconing interval calculated through Eq. (11). Therefore, we can also make a conclusion that beaconing control strategy DBCEC-C performs well in terms of deciding the optimal beaconing frequency under the different message TTLs. In other words, beaconing frequency calculated by Eq. (11) can still maximize delivery rate under the different message TTLs.

Fig. 6-(b) displays the variation of average delay along with the growth of beaconing intervals under different message TTLs. From the simulation results, we can find that the average delay increases along with the growth of the beaconing intervals, which is reasonable and natural according to the above analysis. Similarly, there is still an obvious turning point during the variation process of the average delay. It is not difficult to find that the turning point is precisely the optimal beaconing interval under different message TTLs. For example, when the message TTL is 2500s, the average delay mushrooms along with the increase of beaconing interval from 1s to 125s, and then slowly increases with the increase of beaconing interval from 125s to 800s. In conclusion, the dynamic beaconing control strategy in energy-constrained DTNs (DBCEC) not only optimizes the delivery rate, but also improves the average delay to some extent.

Fig. 6-(c) depicts how the survival time varies with the increase of beaconing intervals under different message TTLs. We omit the detail description for the Fig. 6-(c) due to the reason that the curve shape of Fig. 6-(c) is similar to the one in Fig. 5-(c).

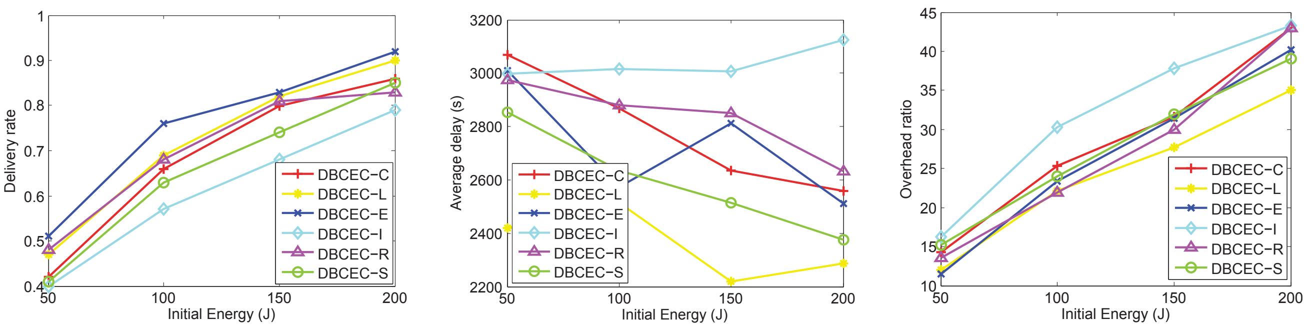
In summary, the beaconing control strategy DBCEC under the random-waypoint mobility pattern can improve the delivery rate and survival time without affecting the average delay with both the different initial energy and message TTLs.

To further compare the six beaconing control strategies: DBCEC-C, DBCEC-L, DBCEC-E, DBCEC-I, DBCEC-R, and DBCEC-S, we conduct simulations regarding the performances of delivery rate, average delay and overhead ratio in Fig. 7 under different initial energy. The initial energy for each node is set to 50J, 100J, 150J, and 200J, respectively. As can be seen in Fig. 7-(a), the delivery rate increases along with the growth of initial energy, which indicates that the initial energy becomes an important factor in terms of the beaconing control strategy. In addition, it is not difficult to find that DBCEC-E achieves the best delivery rate compared with other dynamic beaconing control strategies. Next, Fig. 7-(b) and Fig. 7-(c) provide the important information that DBCEC-E still achieves the similar performances regarding average delay and overhead ratio, compared with other dynamic beaconing control strategies. In conclusion, the simulation results show that, compared with other beaconing control strategies, DBCEC-E achieves the best delivery rate without affecting average delay and overhead ratio.



(a) Delivery rate (b) Average delay (c) Survival time

Fig. 6. Delivery rate, Average delay, and Survival time as a function of beaconing intervals with different TTLs under random-waypoint scenario.



(a) Delivery rate (b) Average delay (c) Overhead ratio

Fig. 7. Delivery rate, Average delay, and Overhead ratio as a function of initial energy for the six different dynamic beaconing control strategies.

TABLE III
SIMULATION PARAMETERS UNDER EPFL SCENARIO

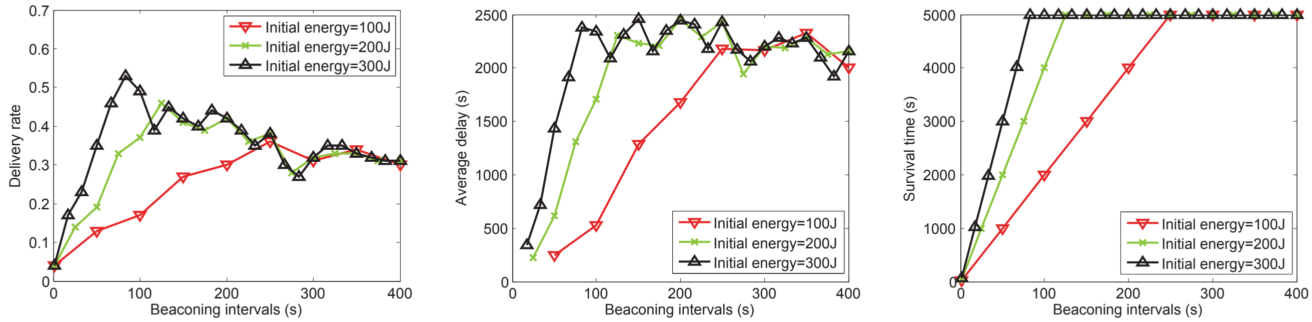
Parameter	**Value**
Simulation time	2500s, 5000s, 7500s
Number of nodes	200
Transmission speed	250kBps
Transmission range	100m
Buffer size	500M
TTL	2500s, 5000s, 7500s
Message size	250kB
Transmission consumption	1J
Beaconing consumption	5J
Energy constraint for each node	100J, 200J, 300J
Mobility speed	2m/s

C. Simulation Analysis Under Epfl Scenario

Epfl contains GPS data from 500 San Francisco taxis acquired over 30 days, without loss of generality; we use the data of the first 200 taxis in this paper. We plug the epfl data set into ONE to simulate taxi mobility over the first 7500s, and the simulation parameters are illustrated in Table III.

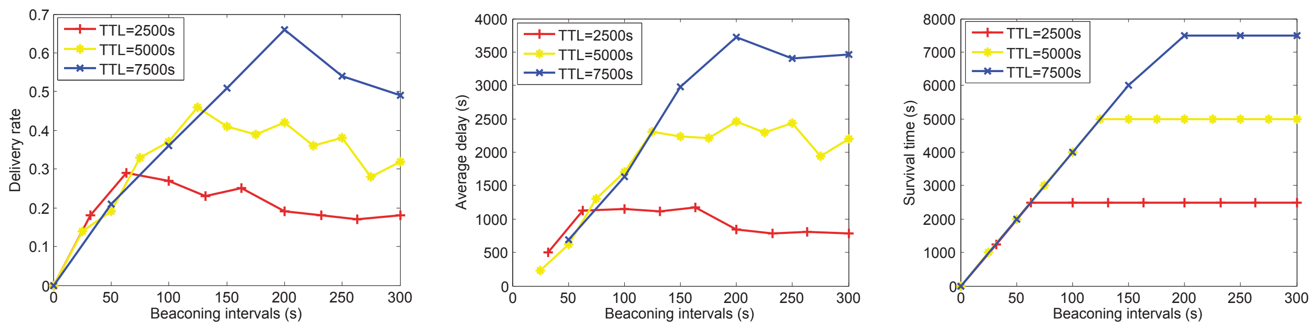
First of all, in the real environment, we set the message TTL to 5000s, and also set the initial energy to 100J, 200J and 300J, respectively. Fig. 8-(a) displays the variation of the delivery rate along with the growth of beaconing intervals under Epfl scenario. The movement of the taxis lacks regularity and the nodes cannot contact each other as frequently as nodes do in the random-waypoint mobility pattern. As a result, some messages cannot be delivered. Thus, the delivery rate obtained in the Epfl scenario significantly differs from that obtained for the synthetic random-waypoint mobility pattern. However, Fig. 8-(a) also shows that delivery rate first increases and then decreases as the beaconing interval increases under Epfl scenario. At the same time, the peak point of the curve precisely matches the value calculated by Eq. (11). Therefore, we can make a conclusion that beaconing control strategy DBCEC still performs well under real mobility traces and has a high accuracy in terms of estimating the optimal beaconing frequency, which is calculated by Eq. (11). The trend of Fig. 8-(b) is similar with that of Fig. 5-(b), which also shows that average delay increases as the beaconing interval increases under Epfl scenario. Fig. 8-(c) shows that as the beaconing interval increases, survival time of the whole network increases linearly. Moreover, we can see that the optimal beaconing interval maximizes the survival time.

Secondly, in the real network environment, the initial energy for each node is set to 200J, and the time-to-live (TTL) for each message is set to 2500s, 5000s, and 7500s, respectively. Fig. 9-(a) shows the changes in delivery rate over the beaconing intervals from 1s to 300s with different message TTLs. Fig. 9-(b) and Fig. 9-(c) display the variation of average delay and survival time along with the growth of the beaconing intervals. We can make a conclusion that the beaconing control strategy DBCEC under the Epfl data set can still improve the delivery rate and survival time without affecting the average delay with both the different initial energy and message TTLs.



(a) Delivery rate (b) Average delay (c) Survival time

Fig. 8. Delivery rate, Average delay, and Survival time as a function of beaconing intervals with different initial energy under Epfl scenario.



(a) Delivery rate (b) Average delay (c) Survival time

Fig. 9. Delivery rate, Average delay, and Survival time as a function of beaconing intervals with different TTLs under Epfl scenario.

VI. Conclusion

In DTNs, the probabilistic nodal mobility and interruptible wireless links lead to nondeterministic and intermittent connectivity. Routing methods always adopt the "store-carry-forward" strategy to forward messages, and a message always has multiple copies. Moreover, frequent beaconing is required to detect the possible contacts (i.e., communication opportunities) and a large number of message copies need to be forwarded ceaselessly. However, this is bound to result in the rapid consumption of energy. Therefore, efficient utilization of energy becomes the key point in DTNs, especially when energy can not be timely supplied. In this paper, in order to maximize the delivery rate, we propose the dynamic beaconing control strategy based on a time-continuous Markov model under the energy-constrained DTNs. Furthermore, simulations are conducted under the synthetic mobility pattern and real mobility traces. The results show that, compared to the other five beaconing control strategies, DBCEC-E can significantly improve the delivery rate without affecting the average delay and the overhead ratio.

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