A Markov Chain Model of Streaming Proxy for Disconnecting Vehicular Networks

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***Abstract*—Frequent loss of network connectivity makes media streaming very challenging in vehicular mobile communication scenarios. It has been shown earlier that a streaming proxy onboard a vehicle can be effective in mitigating the adverse effects of temporary network disconnections. During the connected period, a vehicular proxy pre-fetches as much media as possible ahead of the client's playback time. This pre-fetching is done by utilizing any excess bandwidth in the network connection. The pre-fetched contents are stored in a local storage and played out when the connectivity is temporarily lost. A number of research studies have been conducted to understand the performance dynamics of such streaming proxy systems in vehicular networks, however, no analytical model has been proposed yet. In this paper, we propose a 3-D Markov Chain model to analytically study the performance of such streaming proxies as a function of the system load. The model is validated by means of discrete-event simulation of a realistic networking scenario. The proposed model can be effectively used to dimension the streaming proxy systems in next-generation vehicular networks.**

I. Introduction

The unreliability of network connectivity makes streaming of continuous media from an Internet server to a mobile client extremely challenging. For uninterrupted playback, the client must continue to receive the contents under a strict timing constraint. Unexpected loss of network connectivity during the playback can jeopardize the timing structure of the content causing user irritation.

Streaming proxy is a well known concept that deals with temporary network problems [1]–[3]. The proxy has some storage capability to store pre-fetched content i.e., contents that are fetched from the server ahead of the client's playback time. Provided that a sufficient amount of the content has been pre-fetched and buffered in the local proxy, the client can enjoy uninterrupted playback even during interrupted network connectivity. Streaming proxy can be particularly useful in vehicular mobile communication scenarios, where the network connectivity between a fast moving vehicle and the Internet is likely to experience frequent disruptions. For example, a train with a satellite link will temporarily lose network connectivity each time it goes through a tunnel[1].

Since there may be multitude of users in a vehicle, a central in-vehicle (onboard) streaming proxy is usually shared by all onboard users by means of an onboard vehicular network.One benefit of using a central proxy is the ability to exercise admission control to prevent overloading the satellite link with too many simultaneous streaming sessions. The attractiveness of such admission-controlled streaming proxy has prompted researchers to experiment and study the performance dynamics of such systems under frequent network disconnections [4]–[6]. However, these efforts have been largely confined to simulation-based experiments. Analytical modeling of such systems remains unexplored.

In this paper, *we attempt to analytically model the performance of streaming proxy in vehicular environments, where any excess network (satellite or cellular) bandwidth is fairly shared between all active streaming sessions for pre-fetching purposes*. In particular, we propose a 3-D Markov Chain model that is mathematically tractable yet captures the important behaviours of the streaming system. Using simulations, we demonstrate that the model is valid and capable of predicting the performance of vehicular streaming services accurately. The model can be used as an effective tool to dimension the streaming proxy systems in intermittently connected vehicular networks.

The rest of the paper is organised as follows. Section II provides an overview of the vehicular streaming architecture highlighting the key parameters that influence system performance. The proposed Markov Chain model is presented in Section III followed by its validation in Section IV. Section V presents some key numerical results. Section VI concludes the paper.

II. Vehicular streaming architecture. One central proxy connects many onboard users.

Figure 1 illustrates the proxy-based streaming in vehicular networking scenario using train as an implementation example. All satellite communication services are provided to the user devices through an onboard proxy. The media playback clients are located inside the user devices. The proxy implements a simple admission controller to make sure that the combined bandwidth requirement of all accepted streaming sessions does not exceed the satellite link capacity. The admission controller therefore ensures bandwidth availability for all accepted streaming sessions at the expense of the possibility that a new streaming request may be blocked. The proxy

[1]For reliable operation, satellite links require clear line-of-sight. A car equipped with high-speed cellular data link may also lose connectivity in tunnels or locations with poor radio propagation or high competition

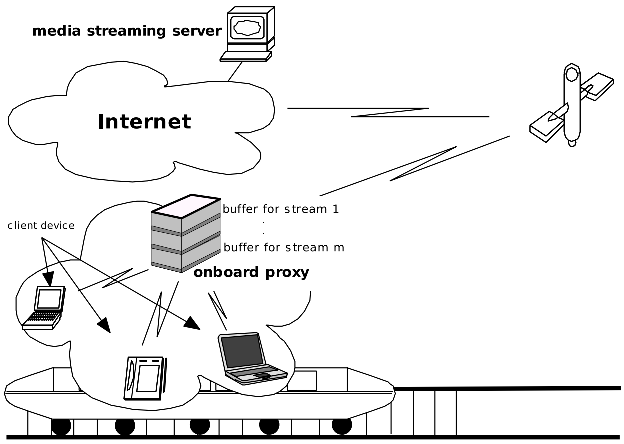


Fig. 1. Vehicular streaming architecture.

decouples the media download, from the Internet server over the satellite link, from the media transfer between the proxy and playback client. The clients transfer contents from the proxy at the natural playout speed of the media. On the other hand, the proxy may use a higher transmission speed to download the media if there is excess bandwidth in the satellite link. Any excess bandwidth is fairly shared between all active connections.

The contents downloaded in advance of the playback are referred to as *prefetched* contents. For each active user streaming session, the proxy maintains a local buffer (storage) to store the pre-fetched content, which is played out by the client at the playout rate. It is assumed that there is always enough buffer to store the pre-fetched contents.

A vehicle entering a tunnel experiences complete *outage* until it re-establishes the line-of-sight with the satellite. During an outage, the proxy ceases its download, but the clients can continue the playback as long as there is content in the proxy buffer. Thus a client faces interruption or playback *blackout* only if its buffer in the proxy runs out of contents during a network outage. Note that, with the streaming proxy onboard, an *outage* does not necessarily mean a *blackout*.

III. Markov Chain Model

In this section, we detail the proposed analytical model that captures the behavior of the streaming proxy.

A. Assumptions

In practical systems all streaming sessions are expected to terminate after a fixed playout length. However such terminating sessions make it difficult to study the *steady state* blackout performance experienced by the clients. To address this issue, we have assumed one *non-terminating* client that never vacates the system. In other words, we consider that there is an observing client who remains connected to the media streaming services from the beginning of the vehicular trip till the end. The evaluation of the proposed model through simulation based experiments show that the only impact of this assumption on the performance of streaming proxy is the reduction of the capacity by one session. This capacity of one session is consumed by the *non-terminating* client during the entire trip time. The assumption of a non-terminating client enables us to model the behavior of streaming proxy as a steady state 3-D markov chain model.

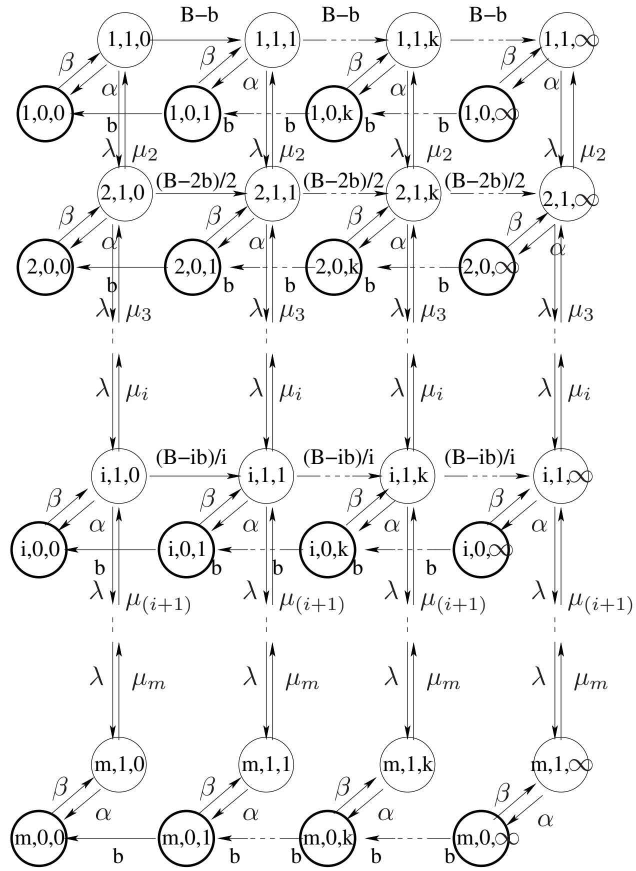


Fig. 2. Markov Chain model of intermittently connected admission-controlled fair-bandwidth-share streaming proxy.

We assume that the playout rate of each client is same and equals b media units/sec. We further assume that the streaming proxy has infinite buffering capacity. Note that this assumption ensures that the lack of buffer should not be a contributing factor in blackout events experienced by the client. This assumption does not limit the model in any way.

B. Notations

Suppose the download capacity of the proxy is B media units/sec. Since the playout rate of each client is b media units/sec, the proxy can accommodate a fixed number of clients m where $m = \frac{B}{b}$. Let α^{-1} be the mean outage duration of the network connection and β^{-1} be the mean connectivity duration. Suppose the mean playout duration of the streaming session is μ^{-1}. Furthermore, suppose the streaming session requests arrive at the proxy with a mean arrival rate of λ. Let $\pi(i, j, k)$ be the steady state probability of the system in state (i, j, k) (the dimensions of the state are explained in next section). The notations used in the paper are summarized in

TABLE I
SUMMARY OF NOTATIONS

parameters	definition
α^{-1}	mean outage duration
β^{-1}	mean connectivity duration
μ^{-1}	mean stream playout length
λ	request arrival rate
B	satellite capacity in media units per sec.
b	playout rate in media units per sec.
m	satellite capacity in number of simultaneous streaming sessions ($\frac{B}{b}$)
$\pi_{(i,j,k)}$	steady state probability of state (i,j,k)

Table I.

C. State Transition Rates

The proposed 3-D Markov Chain model is shown in Figure 2. The model captures the buffer dynamics of the non-terminating client in the streaming proxy (referred to as system) with arrival and departure of the users, and variation in network connectivity. The state of the non-terminating client in the system can be represented by the triplet (i,j,k) where i is the number of active streaming sessions in the system, including the non-terminating client. j is a Boolean variable with 1 representing a connected period and 0 representing an outage period of the network link. k is the number of media units waiting in the buffer of the *non-terminating* client. For example, state $(2,0,3)$ means: there is two active streaming sessions in the system, one of them is the *non-terminating* client, the system is experiencing network outage and three buffered media units exist in the buffer of *non-terminating* client. The probability $\pi_{(2,0,3)}$ is the steady state probability of the non-terminating client being in the state $(2,0,3)$ of the model.

State Transitions $(i,1,k) \rightarrow \{(i+1,1,k),(i-1,1,k)\}$*:* These transitions describe the arrival and departure of the clients from the system. The non-terminating client transits from a state of i streaming sessions in the system to $(i+1)$, with a rate of λ, where $\frac{1}{\lambda}$ is the inter-arrival time of service requests. The inter-arrival times are independent and identically distributed random variables. The system transits from i streaming sessions to $(i-1)$ with a rate of μ_i. $\frac{1}{\mu_i}$ specifies the stochastic process, which describes the length of time that a client occupies a streaming session in the system. Note that the excess bandwidth available in the network connection can be used to download the media faster than the usual playout rate of the clients. Therefore, the session completion rate μ_i in our model is dependent on i (number of active streaming sessions). If the fair-bandwidth-share is assumed for all clients for the pre-fetched data, then the value of μ_i is obtained using Equation (1). Note that no users are admitted in the outage state.

$$\mu_i = \mu \cdot \frac{B}{i \cdot b} \tag{1}$$

State Transitions $(i,1,k) \rightarrow \{(i,1,k+1),(i,j,k-1)\}$*:* These transitions describe the buffer dynamics of the non-terminating client. The buffer of the client grows with a rate of $\frac{B-ib}{i}$, where i is the current number of active sessions in the system. Note that the excess bandwidth capacity $B-ib$ is equally distributed amongst all active sessions. Furthermore, the data is buffered only during connectivity states of the system. The buffer of the non-terminating session is drained during the outage duration of network with a rate of b (the playout rate of client), as indicated in Figure 2.

State Transitions $(i,1,k) \rightarrow (i,0,k)$ *and* $(i,0,k) \rightarrow (i,1,k)$*:* The non-terminating session goes into outage state from a connected state with a rate of α. The transition from outage state to connected state is achieved with a rate of β.

D. Steady State Solution

The normalization and equilibrium conditions of the markov chain model are given by Equations (2) and (3), respectively.

$$\sum \pi_{(i,j,k)} = 1 \qquad 0\le i\le m,\ 0\le j \le 1,\ 0\le k\le \infty \tag{2}$$

The system of linear Equations (2) and (3) can be solved numerically to obtain the steady state probabilities [7]. Note that although the model assumes that the buffer of the non-terminating user (and consequently that of streaming proxy) can grow infinitely, a finite value must be used when solving the system of linear equations. The implications of selecting this value are discussed in the next section. The blackout probability $P_{blackout}$ of the non-terminating client can be obtained from the numerical values of the steady state probabilities using the Equation (4).

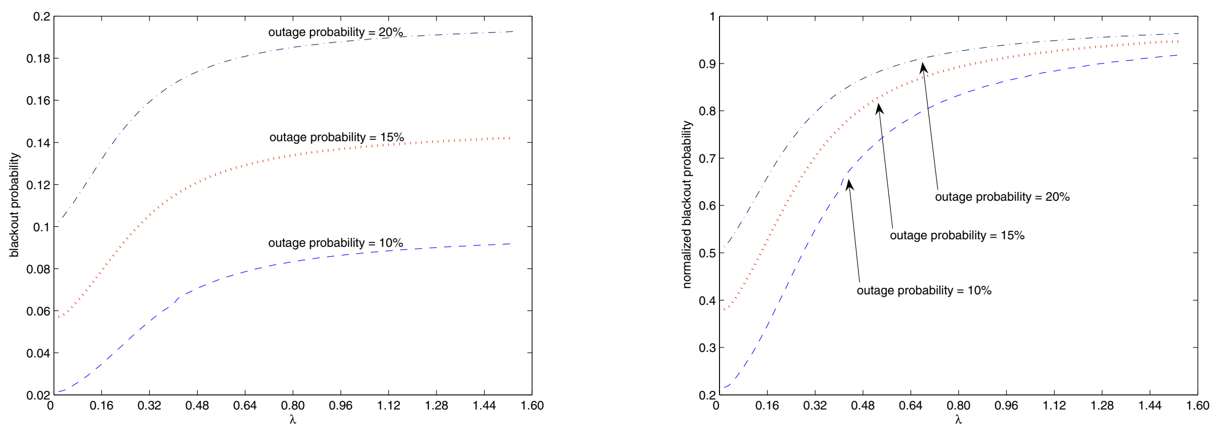
$$P_{blackout} = \sum_{i=1}^{m} \pi_{(i,0,0)} \tag{4}$$

IV. Model Validation

To validate the model, we have developed a discrete-event simulation program that closely simulates the proxy-based streaming scheme described in Section II. One notable difference between the Markov Chain and the simulation model is that all sessions in the simulation are terminating as expected in practical systems. Stream requests follow the Poisson arrival model with exponentially distributed stream (playout) lengths. For the purposes of the admission control, the clients vacate the satellite system as soon as the entire media is downloaded from the Internet server. In other words, although a client may be in the middle of playing out the media from the proxy buffer, the streaming session is considered terminated as far as the satellite link is concerned if there remains no more content to download for the stream. In the simulation, we compute the blackout probability as the fraction of admitted streams that suffered playback blackout due to lack of contents in the proxy buffer during a network outage.

We have simulated a satellite link that can concurrently support four streams (four-channel link). The natural playout rate of a stream is assumed 1 data unit/second, but the download rate can be more than this rate when there is less than four sessions in the system. The network connectivity is modeled as a two-state Markov model where the link alternates between connected and disconnected states, spending a random amount

$$\pi_{(i,j,k)} = \begin{cases} \frac{1}{\alpha}(\beta\pi_{(i,j+1,k)} + (\frac{B}{m})\pi_{(i,j,k+1)}) & 1\leq i \leq m,\ j = 0,\ k = 0 \\ (\frac{1}{\alpha+\frac{B}{m}})(\beta\pi_{(i,j+1,k)} + (\frac{B}{m})\pi_{(i,j,k+1)}) & 1\leq i \leq m,\ j = 0,\ 0< k < \infty \\ (\frac{\beta}{\alpha+\frac{B}{m}})\pi_{(i,j+1,k)} & 1\leq i \leq m,\ j = 0,\ \text{k}= \infty \\ (\frac{1}{\beta+\mu_i})(\alpha\pi_{(i,j-1,k)} + \lambda\pi_{(i-1,j,k)}) & i = m,\ j = 1,\ 0\leq k \leq \infty \\ (\frac{1}{\lambda+\beta+(\frac{B}{i}-\frac{B}{m})})(\alpha\pi_{(i,j-1,k)} + \mu_{(i+1)}\pi_{(i+1,j,k)}) & i = 1,\ j = 1,\ k = 0 \\ (\frac{1}{\lambda+\mu_i+\beta+(\frac{B}{i}-\frac{B}{m})})(\alpha\pi_{(i,j-1,k)} + \mu_{(i+1)}\pi_{(i+1,j,k)} + \lambda\pi_{(i-1,j,k)}) & 1 < i < m,\ j = 1,\ k = 0 \\ (\frac{1}{\lambda+\beta+(\frac{B}{i}-\frac{B}{m})})(\alpha\pi_{(i,j-1,k)} + \mu_{(i+1)}\pi_{(i+1,j,k)} + (\frac{B}{i} - \frac{B}{m})\pi_{(i,j,k-1)}) & i = 1,\ j = 1,\ 0< k < \infty \\ (\frac{1}{\lambda+\mu_i+\beta+(\frac{B}{i}-\frac{B}{m})})(\alpha\pi_{(i,j-1,k)} + \mu_{(i+1)}\pi_{(i+1,j,k)} + \lambda\pi_{(i-1,j,k)} + (\frac{B}{i} - \frac{B}{m})\pi_{(i,j,k-1)}) & 1 < i < m,\ j = 1,\ 0 < k < \infty \\ (\frac{1}{\beta+\lambda})(\alpha\pi_{(i,j-1,k)} + \mu_{(i+1)}\pi_{(i+1,j,k)} + (\frac{B}{i} - \frac{B}{m})\pi_{(i,j,k-1)}) & i = 1,\ j = 1,\ k = \infty \\ (\frac{1}{\beta+\lambda+\mu_i})(\alpha\pi_{(i,j-1,k)} + \mu_{(i+1)}\pi_{(i+1,j,k)} + \lambda\pi_{(i-1,j,k)} + (\frac{B}{i} - \frac{B}{m})\pi_{(i,j,k-1)}) & 1 < i < m,\ j = 1,\ k = \infty \end{cases} \quad (3)$$



(a) (b)

Fig. 3. Blackout probability as a function of system load (μ^{-1} = 25, β^{-1} = 1000, m = 4, b = 1)

of time in each state that is distributed exponentially with a mean of β^{-1} and α^{-1}, respectively.

Before we proceed to comparing the model output with simulation results, we must remember one important peculiarity of the proposed Markov Chain model as explained in the previous section. Recall that, for practical purposes, we will have to select an appropriate threshold, Δ, for the third dimension of the Markov Chain to solve the recursive balance equations.

Figure 4 compares the blackout probabilities derived from the proposed Markov Chain model (for three different Δ values) with the ones obtained from the simulation experiments. We observe that the parameter Δ has a significant effect on the accuracy of the model. It is evident that the proposed model can produce very accurate results when the parameter Δ is selected appropriately (Δ = 175 in this case). For a Δ that is too high, the model underestimates the performance and vice versa.

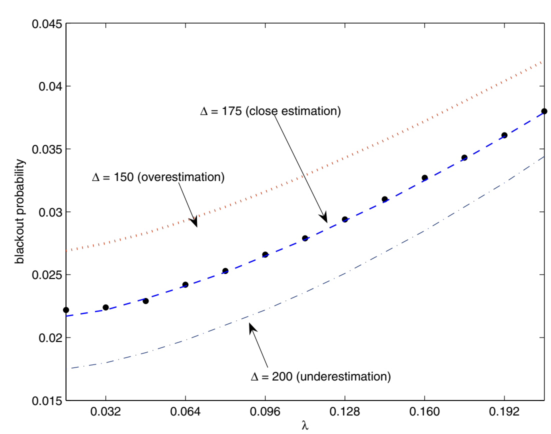


Fig. 4. Comparison of analytical and simulation results (μ^{-1} = 25, β^{-1} = 1000, α^{-1} = 111, m = 4, b = 1)

V. Numerical Experiments

In this section, we explore some of the fundamental properties of the fair-bandwidth-share streaming proxy using a series of numerical experiments. Figure 3a shows the streaming blackout probability as a function of the system load for different network outage probability, where outage probabil-

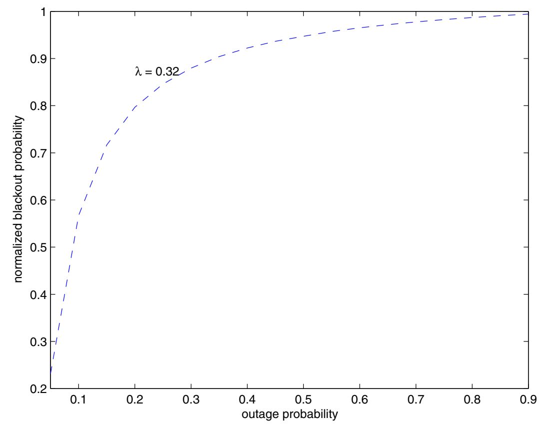


Fig. 5. Normalized blackout probability versus outage probability (μ^{-1} = 25, β^{-1} = 1000, m = 4, b = 1)

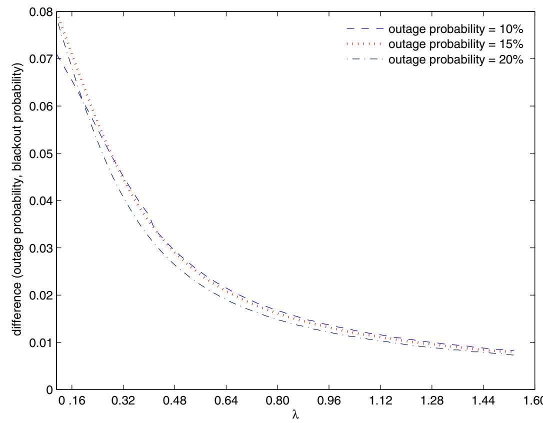


Fig. 6. Difference between outage probability and blackout probability (μ^{-1} = 25, β^{-1} = 1000, m = 4, b = 1)

ity is defined as the fraction of time the network remains disconnected (computed as $\frac{\alpha^{-1}}{\alpha^{-1}+\beta^{-1}}$). It can be seen that the effect of the proxy is most pronounced under low traffic scenarios, where the probability that a streaming application experiences blackout is significantly lower than the outage probability. For example, for a request arrival rate of 0.16, the probability of a streaming session to actually face a playback blackout is less than 4% even when the network has a 10% probability to face outage. In otherwords, the proxy in this case has *effectively* reduced the outage probability by 60%. The decreasing effectiveness of the proxy with increasing load is intuitively expected because any difference between the media download speed and the playout speed diminishes with increasing load. Clearly, the network bandwidth has to be dimensioned properly to ensure that the streaming proxy can deliver the desired blackout probability.

We now turn to answer an important question. For a given load and network bandwidth, can a vehicular network enjoy the identical percentage reduction in the effective outage probability irrespective of the actual outage probability? We find the answer to this question when the blackout probability is normalized to the outage probability (Figure 3b). It can be seen that the impact of streaming proxy in terms of percentage reduction in the effective outage probability is more severe in networks that face outage less frequently. This result is better illustrated in Figure 5 which shows the normalized blackout probability as a function of outage probability for a particular system load ($\lambda = 0.32$) and network bandwidth ($m = 4$).

To better explain why the streaming proxy has a more pronounced benefit for less frequently disconnected networks, we plot the difference between the outage and blackout probabilities, which represents the "outage reduction capability" (ORC) of the proxy (Figure 6). We can see that although the ORC decreases with increasing system load (as expected intuitively), it remains independent of the outage probability. As a consequence, higher the outage probability, the less is the *percentage* reduction in the effective outage probability faced by the streaming sessions. Indeed, for a given outage probability and system load, network bandwidth has to be dimensioned carefully to kepp the blackout probability below the target threshold.

VI. Conclusion and Future Work

In this paper, we have proposed a 3-D Markov Chain model that captures the performance of proxy-based streaming in frequently disconnected mobile communication scenarios. By means of simulation, we have shown that the model is valid and can accurately predict the performance of the fair-bandwidth-share streaming proxy. One limitation of the proposed model is its dependence on correct tuning of the third dimension (Δ parameter). In this paper, we tuned the parameter experimentally with help from simulation. Analytical derivation of the Δ parameter would constitute an interesting and useful future work.

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