Optimal Pending Interest Table Size for ICN with Mobile Producers

Vignesh Sivaraman[1], Dibyajyoti Guha[1 2], and Biplab Sikdar[1]

[1]Department of Electrical and Computer Engineering, National University of Singapore, Singapore, 117583
[2] Department of Information Techonology, International Management Institute Kolkata, India, 700027

***Abstract*—Many next generation Internet architectures exist in the literature for addressing various issues like increasing traffic, mobility and efficient content dissemination. One such emerging fundamental design is Information Centric Networking (ICN). The Pending Interest Table (PIT) is one of the essential components of the ICN forwarding plane responsible for the stateful routing in ICN. Optimal size of the PIT is essential for the efficient performance of the network and the enhanced consumer experience. Therefore, the optimal sizing of the PIT under various network conditions is an important and challenging problem. To this end, this paper models the PIT of a router as a $GI/M/c/N$ queue. The model has (i) a general arrival process to accommodate the diverse nature of traffic, (ii) a service time model which takes into account the caching at the content stores and the mobility of producers, and (iii) a sojourn time distribution which is used to characterize the content delivery time at the consumers. Using the $GI/M/c/N$ queueing model, we formulate an optimization problem to minimize the PIT size while subjecting the interest drop probability to an upper bound. The accuracy of our analytical model is demonstrated using simulations on different Internet Service Provider (ISP) topologies across a wide range of system parameters.**

***Index Terms*—Information centric networks, pending interest table, optimal PIT sizing, queueing theory, mobile producer.**

I. Introduction

Efficient distribution and retrieval of multimedia content in the current host centric Internet architecture needs different solutions like content distribution networks, peer-to-peer networks, etc. The focus of many ongoing research has shifted from the host to the content. Most of the proposed content-centric architectures for the future Internet have "named-data" as the principle element of the architecture. Of many such proposed architectures in this direction, Information Centric Networking is one. In content centric networks like ICN, the consumer only needs to know "what" is the content unlike the current Internet in which the consumer is required to know "where" the content located as well [1]. ICN has the following unique characteristics which are fundamental for the efficient dissemination of contents: (i) Content's identity and its location are decoupled; (ii) The transport of content is consumer driven, i.e., each content has to be explicitly asked for by the consumer; (iii) The content traverses the reverse path of its corresponding request (also referred to as interest); (iv) Content is cached at the content stores of the intermediate nodes in the network (in-network caching).

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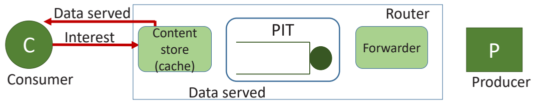
The Pending Interest Table (PIT) is one of the essential components of the ICN forwarding plane responsible for the stateful routing in ICN. The PIT carries out the following functions: (i) routing the content on the interest's reverse path, (ii) aggregation of interests, (iii) other forwarding tasks like loop detection etc. PIT sizes are finite and if they are not dimensioned properly, interests arriving at a router may experience unacceptably high drop rates. Interests dropped at routers adversely affect the quality of experience of the consumer since the dropped interest needs to be retransmitted, and as a result, the delay experienced by the consumer increases. Moreover, the interest dropped at the PIT of one router might still be using up resources at other routers (by being present at their PITs). The PIT is a component of the ICN forwarding plane and is required to function at the wire-speed, thereby making the PIT an expensive resource whose cost increases with its increasing size. Therefore, designing the PIT size for minimizing the incurred cost while considering the interest drop rate is an important problem to be addressed.

Mobile data traffic forms a significant fraction of the total IP traffic. CISCO Visual Networking index forecasts that by 2021, traffic from mobile and wireless devices will account for 63% of the total IP traffic [2]. Support for mobility has become an integral requirement for any Internet architecture. In ICN, support for consumer mobility is inherent and there are many proposals for supporting producer mobility [3]–[7]. To this end, the discussions in our work consider both stationary as well as mobile producers.

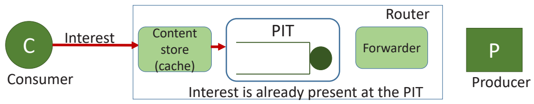
A. Contributions

The contributions of this work are as follows:

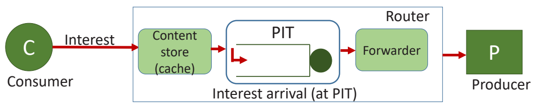
- We model the PIT occupancy as a $GI/M/c/N$ queue. We discuss two queueing models in detail. The first model considers implicit interest timeouts and the second model has explicit interest timeouts.
- Our queueing model takes into consideration the caching at the content stores and the possibility of producer mobility while modeling the queue's service time.
- We use this queueing model to formulate an optimization problem to minimize the PIT size at the router while subjecting the interest drop probability to an upper bound.
- We extend this queueing model to characterize the distribution of content delivery time as experienced by the consumers.



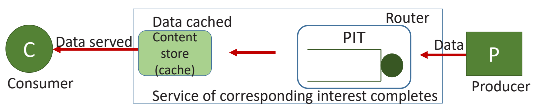
(a) Cache hit at the router



(b) PIT hit at the router



(c) Cache and PIT miss at the router



(d) Data processing at the router

Fig. 1. Different scenarios at the ICN routers.

- We perform extensive simulations using different ISP topologies and network conditions to evaluate the accuracy of our proposed queueing and optimization model.

The rest of the paper is organized as follows. In Section II we discuss the existing literature related to our work. Then, in Section III we develop our queueing and optimization model for calculating the optimal PIT size at the router and we discuss the distribution of content delivery time as experienced by the consumers. The input process for interest generation in the simulations is discussed in Section IV. The performed simulations and our findings are discussed in detail in Section V and Section VI concludes the paper.

II. Background and Related Work

A. ICN Background

In this section, we briefly describe the working of ICN. ICN requires every content to be uniquely named which is used by consumers for retrieving them. Consumers generate an Interest with the unique name in order to request for the content. The content producers respond with the corresponding Data. When an interest arrives at a router, the router first looks for the content in its own cache called the Content Store (CS). If a hit occurs, the router replies with the data as depicted by Figure 1a. In case of a miss, the router looks up the PIT which stores the information to map the pending interests (interests for which data is not yet received) with their corresponding incoming links. If an interest is already pending for the content, then the entry in the PIT is updated to accommodate the new interest but no new interest is forwarded by the router as shown in Figure 1b. If no match is found in the PIT, the router adds an entry for the interest into the PIT. It then looks up the Forwarding Information Base (FIB) which maps name prefixes to the next hop router and finally forwards the interest to the next hop router as depicted in Figure 1c. When a data packet arrives, a router looks up the PIT for any matching entires. If found, the router sends the data back to the requesting router and caches the data in its CS as shown in Figure 1d. Otherwise, the data is considered to be unsolicited and is dropped.

B. Related Work

The sizing of router buffers for TCP/IP networks is a well explored problem in the literature [8]–[10]. In ICN routers, the PIT can be viewed as a buffer where information about the pending interests is stored. The PIT is looked up on the arrival of a data packet. These operations are required to be performed at wire-speed. The optimal dimensioning of PIT is an important problem because of the trade-off between the cost of its wire-speed implementation and the achieved performance. Authors in [11]–[15] discuss the problem of wire-speed implementation of PIT.

Prior to our work, the problem of optimal dimensioning of PIT has been addressed in [16]–[18]. Authors in [16] systematically evaluate the usability of the existing router components for the support of Content Centric Networks. Their evaluation addresses the three main components of ICN routers, i.e., FIB, CS and PIT. Considering parameters like interest arrival and data response rate, they discuss a primitive model for different metrics like PIT hit probability and PIT miss probability. Using these metrics, the authors evaluate the worst case memory size required for the PIT. In contrast to our work, authors do not analytically model the PIT occupancy.

Authors in [17] present an analytical model for the PIT. They adopt a deterministic fluid model to represent the packet flows as a continuous flows. They assume that the interest flows follow a sliding window protocol similar to that of TCP. Using these assumptions, they describe the PIT state using Delay Differential Equations and estimate the average and the maximum PIT size taking into account the interest drop probability. We note that the authors assume the interest and data packets to be continuous flows and study the PIT with no caching nor PIT timeouts. In our work we aim to address these gaps by modeling the PIT as a $GI/M/c/N$ queue with interest timeouts and considering caching at the routers while estimating the mean service time.

The authors in [18] develop a Markov model for the PIT occupancy with interest timeouts and retransmissions. They assume the interest arrivals to follow a Poisson distribution and the interest service time to be exponentially distributed. Using these assumptions, they model the PIT using a two-dimensional continuous time Markov chain and estimate the interest drop probability. While their model takes into account various factors of ICN like in-network caching, interest drop probabilities and interest time-outs, the authors assume the interest arrivals to be Poisson distributed. We compare our proposed model for PIT occupancy with this model.

Although authors in [17], [18] address the problem of optimal PIT size by analytically modeling PIT occupancy taking interest drop probability into account, there is no work in the literature which models the PIT occupancy as a queue (i) with general arrival process, (ii) whose service time accounts for the caching at the content stores, interest time-outs and the mobility of the producer, (iii) which can be extended to evaluate the sojourn time distribution at the consumer. This paper addresses these gaps in existing literature.

III. PIT Occupancy

In this section we model PIT occupancy using two queueing models and formulate an optimization problem to determine the optimal PIT size. First, we model the PIT occupancy as a $GI/M/c/N$ queue and then we extend this model to accommodate for interest timeouts. The service time distribution (discussed in detail in Section III-D) of this queue accounts for the content stores in the routers and the mobility of producer nodes.

A. PIT occupancy model

In this section we describe in detail our $GI/M/c/N$ queue model for PIT occupancy [19].

Let the size of the PIT be c interests, i.e., there can be a maximum of c interests that have been forwarded by the router and are yet to receive their corresponding contents. In our model, we also allow for an additional buffer of K interests, i.e., the interests in the buffer are yet to be forwarded by the router. Hence, we have $N = c + K$. When the PIT is full, the additional buffer stores (upto K) new interest arrivals, while waiting for space (server) to become available in the PIT (or the interest timeout). In the absence of such additional buffers, interests that arrive when the PIT is full are dropped and need to be retransmitted by the consumer. In many of the existing literature [17], [18], the PIT does not have any extra buffer available. To accommodate such a system, we can set $K = 0$ and our model becomes a $GI/M/c/c$ queue. We assume that the time required for a requested interest to be served (also referred to as the service time) follows an exponential distribution with mean μ. Estimation of μ is discussed in Section III-D. In order to account for traffic of diverse nature, we consider a general arrival process. The inter-arrival time between any two interests is an independently and identically distributed (i.i.d) random variable having a general distribution $A(u)$ $(u \geq 0)$, a probability density function (pdf) $a(u)$ $(u \geq 0)$, Laplace-Stieltjes transform (LST) $A^*(\theta)$, and mean $1/\lambda$. Let $\{t_0, t_1, t_2, \cdots\}$ be the successive interest arrival epochs and $\{t_0^-, t_1^-, t_2^-, \cdots\}$ be the pre-arrival epoch (time epoch just before the arrival instant). We consider $t_n^-,\ n > 0$ to be the embedded points for the system. Let $N(t_n^-)$ be the number of interests in the PIT at the time epoch t_n^-. We define the state of the system at time t as $N(t)$. It can be easily observed that the process $\{N(t_n^-)\}$ is an embedded Markov chain. Let the probability that the PIT is in state n at the pre-arrival epoch be denoted by π_n^-.

We consider the following exhaustive scenarios:

1) PIT is full (all servers are busy) during an inter-arrival time: Let d_k $(k \geq 0)$ be the probability that k interests are served between two consecutive interest arrivals, given that the number of interests in the system during this time duration is greater than or equal to c. Note that in this interval the effective service time is $c\mu$.
2) PIT is not full during an inter-arrival time:
   a) PIT is not full before the start of the inter-arrival time: Let $a_{k,j}$ be the probability that an arriving interest finds the system in state $k-1$ $(1 \leq k \leq c)$, while the next arriving interest finds the PIT in state j $(0 \leq j \leq k)$. It implies that service time of j interests out of existing k interests is more than the inter-arrival time, and $k-j$ interests have been served during the inter-arrival time of an interest.
   b) PIT is full before the start of the inter-arrival time: Similarly, $b_{k,j}$ is the probability that an arriving interest finds the system in state $k-1$ $(c < k \leq N)$, and the next arriving interest finds the PIT in state j $(0 \leq j \leq c)$.

We calculate $d_k, a_{k,j}$, and $b_{k,j}$ as follows

$$\begin{aligned}
a_{k,j} &= P(N(t_n^-) = j | N(t_{n-1}^-) = k-1) \\
&\qquad \text{where } (1 \leq k \leq c),\ (0 \leq j \leq k) \\
&= \int_0^\infty \binom{k}{j} e^{-\mu j t} (-1)^{k-j} (e^{-\mu t} - 1)^{k-j} dA(t) \\
&= \int_0^\infty \binom{k}{j} e^{-\mu j t} (-1)^{k-j} . \\
&\qquad \sum_{l=0}^{k-j} \binom{k-j}{l} e^{-\mu t (k-j-l)} (-1)^l dA(t) \\
&= \int_0^\infty \binom{k}{j} \sum_{l=0}^{k-j} (-1)^{k-j+l} \binom{k-j}{l} e^{-\mu t (k-j-l+j)} dA(t) \\
&= \binom{k}{j} \sum_{l=0}^{k-j} (-1)^{k-j+l} \binom{k-j}{l} \int_0^\infty e^{-\mu t (k-l)} dA(t) \\
&= \binom{k}{j} \sum_{l=0}^{k-j} (-1)^{k-j+l} \binom{k-j}{l} a^*(\mu(k-l)) \qquad (1)
\end{aligned}$$

$$d_k = \int_0^\infty \frac{(c\mu t)^k}{k!} e^{-c\mu t} dA(t), \qquad (2)$$

$$\begin{aligned}
b_{k,j} &= P(N(t_n^-) = j | N(t_{n-1}^-) = k-1) \\
&\qquad \text{where } (c < k \leq N),\ (0 \leq j \leq c), \\
&= \int_0^\infty \int_0^t \frac{(\mu c)^{k-c} u^{k-c-1} e^{-c\mu u}}{(k-c-1)!} \binom{c}{j} e^{-\mu j (t-u)} . \\
&\qquad (1 - e^{-\mu(t-u)})^{c-j} du\ dA(t) \\
&= \frac{(\mu c)^{k-c}}{(k-c-1)!} \binom{c}{j} \int_0^\infty \int_0^t g(u) h(t-u) du\ dA(t), \qquad (3)
\end{aligned}$$

where $g(u) = e^{-c\mu u} u^{k-c-1}$ and $h(t-u) = e^{-\mu j (t-u)} (1 - e^{-\mu(t-u)})^{c-j}$. The second integral is the convolution of $g(u)$ and $h(t-u)$, and thus the whole integral is the LST of the convolution of these two functions [20]. The LST of $g(t)$ can be computed as

$$\int_0^\infty e^{-st} e^{-c\mu t} t^{k-c-1} dt = \frac{(k-c-1)!}{(s+c\mu)^{k-c}}.$$

Similarly, the LST of $h(t)$ can be obtained as

$$\int_0^\infty e^{-st} h(t) dt = \int_0^\infty e^{-st} e^{-\mu j t} (1 - e^{-\mu t})^{c-j} dt$$

PIT occupancy model	
c	PIT size (number of servers at the PIT)
K	Additional buffer size at PIT
N	System size at the PIT (sum of the number of servers and buffer at the PIT)
$A(u)$	Distribution function of the inter-arrival time between two interests at the consumer
$a(u)$	Probability density function of the inter-arrival time between two interests at the consumer
$A^*(\theta)$	Laplace-Stieltjes transform of $a(u)$
λ	Mean interest arrival rate at the consumer
π_n	Probability that the number of interests in the PIT is n
d_k	Probability that k interests are served between two consecutive interest arrivals, given that the PIT is fully occupied
$a_{k,j}$	Probability that an arriving interest finds PIT in state $k-1, (1 \leq k \leq c)$ and the next interest finds PIT in state $j, (0 \leq j \leq k)$
$b_{k,j}$	Probability that an arriving interest finds PIT in state $k-1, (c < k \leq N)$ and the next interest finds PIT in state $j, (0 \leq j \leq c)$
$m_{i,j}$	i^{th} row and j^{th} column element of the Transistion Probability Matrix
μ	Mean service time of the PIT
PIT occupancy model with timeouts	
$\boldsymbol{\pi}$	Stationary Probability Vector for the PIT.
$\boldsymbol{\pi}^*$	Laplace-Stieltjes transform of $\boldsymbol{\pi}$
α	Mean interest timeout time
Estimation of mean service time	
C_i	The cache size of the i^{th} router
κ	Content popularity class
S	Number of contents in every content class
σ	Average content size
z	Zipf's constant
$m_k(i)$	Cache miss rate for content class κ at router i
B_i^j	Bandwidth of the link between routers i and j
R_i^j	Propagation delay between routers i and j
D	Size of the content packet (in bits)
$f(i)$	Probability that the content is served by the i^{th} router
$T_1(n)$	The expected content service time when content is served by the n^{th} router
u_1	Expected amount of time the producer is connected to a given cellular base station or WiFi access point
v	Average speed of the producer
u_2	Expected amount of time the producer is not reachable
q	Probability that the producer is reachable
Sojourn time distribution	
$S(t)$	Distribution function of the sojourn time of the PIT
$F(t)$	Distribution function of the service time of the PIT
$G_k(t)$	Distribution function of the waiting time when the PIT is in state k
Input Process	
Q	Infinitesimal generator of the underlying $m-$ state continuous time Markov chain for the MMPP
$\boldsymbol{\lambda}$	Vector of Poisson arrival rates corresponding to the m states of Markov chain

TABLE I
LIST OF VARIABLES AND SYMBOLS USED

$$= \frac{\Gamma(j + s/\mu)\Gamma(c - j + 1)}{\mu\Gamma(c + s/\mu + 1)}.$$

Let $m_{i,j}$ denotes the probability for the system transitions from system-state i to j between two consecutive arrivals, i.e., $m_{i,j} = P(N(t_n^-) = j | N(t_{n-1}^-) = i)$. Observing the state of the system at two consecutive embedded points, we define the one step transition probability matrix (TPM) $\mathbf{M}$ as:

$$m_{i,j} = \begin{cases} a_{i+1,j} & \text{if } i \leq c-1,\ j \leq i+1 \\ b_{i+1,j} & \text{if } c \leq i \leq N-1,\ j \leq c-1 \\ d_{i-j+1} & \text{if } c \leq i \leq N-1,\ c \leq j \leq i+1\ . \\ m_{i-1,j} & \text{if } i = N,\ j \in 0, 1, .., N \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

Using the TPM, we can solve for the stationary probabilities at the pre-arrival epochs.

We note that when $\lambda \geq c\mu$, the system reaches its buffer capacity in the steady state (as the system is finite) following $m_{i,i+1}$ $0 \leq i \leq N$. As no service is completed during the inter-arrival time $m_{i,i+1} = d_0$.

B. PIT occupancy model with interest timeouts

In this section, we model the PIT as a $GI/M/c/N$ queue with interest timeouts. Let $\boldsymbol{\pi}$ and $\boldsymbol{\pi}^*$ be the stationary probability vector and its LST, respectively. Let the service time and the interest timeout time be exponentially distributed. Let μ and α denote the mean service time and mean interest timeout time.

Let $N(t_n^-)$ be the number of interests in the PIT at the time epoch t_n^- . We define the state of the system at time t as $N(t)$. It can be easily observed that the process $\{N(t_n^-)\}$ is an embedded Markov chain with the state space $\Omega = \{k, 0 \leq k \leq N\}$. Let the probability that the PIT is in state n at the pre-arrival epoch be denoted by π_n^-. It may be noted that the issue of explosivity of Markov chain does not arise in our case as we have a finite queue, which satisfies the condition of non explosivity of Markov Chains [21, Theorem 2.7.1 on p. 90].

The state of the system at an arbitrary time t is described by the following random variables, namely:

- $N(t)$ = number of customers present in the system,
- $U(t)$ = remaining inter-arrival time until the next arrival.

We define the joint probabilities of system-length $N(t)$ and the remaining inter-arrival time $U(t)$ by:

$$\pi_i(u)du = \lim_{t\to\infty} P\Big\{N(t) = i, u \leq U(t) < u + du\Big\}, \qquad u \geq 0,\ 0 \leq i \leq N.$$

Since we discuss the model in steady-state, i.e., when $t \to \infty$, the above probabilities are denoted by π_i, for simplicity.

Let the LST of $\pi_i(u)$ be defined as follows:

$$\pi_i^*(\theta) = \int_0^\infty e^{-\theta u}\pi_i(u)du, \quad 0 \le i \le N.$$

We note that $\pi_i \equiv \pi_i^*(0), \ 0 \le i \le N$. Observing the system between two arbitrary times u and $u - du$ (where u represents the remaining time to an arrival of an interest) which are separated by an infinitesimal small duration and using the Kolmogorov forward equations, we derive the following equations:

$$\begin{aligned}
\pi_0(u-du) &= \pi_0(u) + \mu\pi_1(u)du\\
\pi_i(u-du) &= \Big(1 - i(\mu+\alpha)du\Big)\pi_i(u) + a(u)\pi_{i-1}(0)du\\
&\quad + (i+1)(\mu+\alpha)\pi_{i+1}(u)du, \text{ if } 1 \le i \le c-1,\\
\pi_i(u-du) &= \Big(1 - (c\mu + i\alpha)du\Big)\pi_i(u) + a(u)\pi_{i-1}(0)du\\
&\quad + \Big(c\mu + (i+1)\alpha\Big)\pi_{i+1}(u)du \text{ if } c \le i \le N-1,\\
\pi_N(u-du) &= \Big(1 - (c\mu + N\alpha)du\Big)\pi_N(u)\\
&\quad + a(u)(\pi_{N-1}(0) + \pi_N(0))du.
\end{aligned}$$

To obtain the system-length distributions at arbitrary times, we develop the differential difference equations that relate the distribution of number of customers in the system. For this, we use the remaining inter-arrival time as a supplementary variable and relate the state of the system at two consecutive times u and $u - du$. Hence, the steady-state differential difference equations can be written as:

$$-\frac{d}{du}\boldsymbol{\pi}_0(u) = \mu\boldsymbol{\pi}_1(u) \tag{5}$$

$$\begin{aligned}
-\frac{d}{du}\boldsymbol{\pi}_i(u) &= -i(\mu+\alpha)\boldsymbol{\pi}_i(u) + a(u)\boldsymbol{\pi}_{i-1}(0)\\
&\quad + (i+1)(\mu+\alpha)\boldsymbol{\pi}_{i+1}(u), \quad \text{if } 1 \le i \le c-1
\end{aligned} \tag{6}$$

$$\begin{aligned}
-\frac{d}{du}\boldsymbol{\pi}_i(u) &= -(c\mu + i\alpha)\boldsymbol{\pi}_i(u) + a(u)\boldsymbol{\pi}_{i-1}(0)\\
&\quad + (c\mu + (i+1)\alpha)\boldsymbol{\pi}_{i+1}(u), \text{ if } c \le i \le N-1
\end{aligned} \tag{7}$$

$$\begin{aligned}
-\frac{d}{du}\boldsymbol{\pi}_N(u) &= -(c\mu + N\alpha)\boldsymbol{\pi}_N(u)\\
&\quad + a(u)(\boldsymbol{\pi}_{N-1}(0) + \boldsymbol{\pi}_N(0))
\end{aligned} \tag{8}$$

We use the following relation for the derivations of Equations (10)-(13):

$$\int_0^\infty e^{-\theta u}\frac{d}{du}\boldsymbol{\pi}_i(u)du = \theta\boldsymbol{\pi}_i^*(\theta) - \boldsymbol{\pi}_i(0). \tag{9}$$

Multiplying both sides of Equations (5)-(8) by $e^{-\theta u}du$, integrating with respect to u from 0 to ∞ and using the Equation (9) yields:

$$-\theta\boldsymbol{\pi}_0^*(\theta) = \mu\boldsymbol{\pi}_1^*(\theta) - \boldsymbol{\pi}_0(0) \tag{10}$$

$$\begin{aligned}
(i(\mu+\alpha) - \theta)\boldsymbol{\pi}_i^*(\theta) &= ((i+1)(\mu+\alpha))\boldsymbol{\pi}_{i+1}^*(\theta)\\
&\quad + A^*(\theta)\boldsymbol{\pi}_{i-1}(0) - \boldsymbol{\pi}_i(0),\\
&\quad \text{if } 1 \le i \le c-1
\end{aligned} \tag{11}$$

$$\begin{aligned}
(c\mu + i\alpha - \theta)\boldsymbol{\pi}_i^*(\theta) &= (c\mu + (i+1)\alpha)\boldsymbol{\pi}_{i+1}^*(\theta)\\
&\quad + A^*(\theta)\boldsymbol{\pi}_{i-1}(0) - \boldsymbol{\pi}_i(0),\\
&\quad \text{if } c \le i \le N-1
\end{aligned} \tag{12}$$

$$\begin{aligned}
(c\mu + N\alpha - \theta)\boldsymbol{\pi}_N^*(\theta) &= A^*(\theta)\boldsymbol{\pi}_{N-1}(0)\\
&\quad + A^*(\theta)\boldsymbol{\pi}_N(0) - \boldsymbol{\pi}_N(0).
\end{aligned} \tag{13}$$

By adding Equations (10), (11), (12) and (13), we get the following:

$$\sum_{i=0}^{N}\boldsymbol{\pi}_i^*(\theta) = \frac{1}{\theta}\sum_{i=0}^{N}\left(I - A^*(\theta)\right)\boldsymbol{\pi}_i(0).$$

We evaluate $\boldsymbol{\pi}_i(0)$ and $\boldsymbol{\pi}_i^*(\theta)$ recursively in terms of $\boldsymbol{\pi}_N(0)$ as follows

$$\boldsymbol{\pi}_i(0) = R_i\boldsymbol{\pi}_N(0) \tag{14}$$

$$\boldsymbol{\pi}_i^*(\theta) = S_i\boldsymbol{\pi}_N(0). \tag{15}$$

Let us define δ_i and ζ_i as follows

$$\begin{aligned}
\delta_i &= c\mu + i\alpha, && \text{if } c+1 \le i \le N\\
\zeta_i &= i(\mu+\alpha), && \text{if } 1 \le i \le c.
\end{aligned}$$

After substituting $\theta = \delta_N$ in Equation (13), we get

$$\boldsymbol{\pi}_{N-1}(0) = [A^*(\delta_N)]^{-1}[I - A^*(\delta_N)]\boldsymbol{\pi}_{\boldsymbol{N}}(0). \tag{16}$$

Comparing Equation (14) and Equation (16), we get

$$R_{N-1} = [A^*(\delta_N)]^{-1}[I - A^*(\delta_N)]. \tag{17}$$

We note that A^* is the Laplace-Stieltjes transform of inter-arrival times. As the diagonal elements of the rate transition matrix of the arrival process are greater than or equal to the corresponding row elements, A^* is a non singular matrix and hence the inverse exists. Further, substituting $\theta = \delta_i$ in Equation (12), $\theta = \zeta_i$ in Equation (11) and performing some recursive simplifications, we get

$$R_i = [A^*(\zeta_{i+1})]^{-1}[R_{i+1} - \zeta_{i+2}S_{i+2}(\zeta_{i+1})], \quad \text{if } 1 \le i \le c-1 \tag{18}$$

$$R_i = [A^*(\delta_{i+1})]^{-1}[R_{i+1} - \delta_{i+2}S_{i+2}(\delta_{i+1})], \quad \text{if } \ c \le i \le N-2. \tag{19}$$

Now, using R_{N-1} from Equation (17) and Equation (13) we get

$$S_N(\theta) = \begin{cases} \frac{1}{\delta_N - \theta}[A^*(\delta_N)]^{-1}[A^*(\theta) - A^*(\delta_N)], & \text{if } \theta \ne \delta_N\\ -[R_{N-1} + I][A^{*1}(\theta)], & \text{if } \theta = \delta_N, \end{cases}$$

where $A^{*1}(\theta)$ is the first derivative of $A^*(\theta)$.

For the case $c \le i \le N-1$, we obtain $S_i(\theta)$ using Equation (12) as follows

$$S_i(\theta) = \begin{cases} \frac{1}{\delta_i - \theta}[\delta_{i+1}S_{i+1}(\theta) + R_{i-1}A^*(\theta) - R_i], & \text{if } \theta \ne \delta_i\\ -[\delta_{i+1}S_{i+1}^1(\theta) + R_{i-1}A^{*1}(\theta)], & \text{if } \theta = \delta_i, \end{cases}$$

and for the case $1 \le i \le c-1$, using Equation (11) we obtain

$$S_i(\theta) = \begin{cases} \frac{1}{\zeta_i - \theta}[\delta_{i+1}S_{i+1}(\theta) + R_{i-1}A^*(\theta) - R_i], & \text{if } \theta \ne \zeta_i\\ -[\zeta_{i+1}S_{i+1}^1(\theta) + R_{i-1}A^{*1}(\theta)], & \text{if } \theta = \zeta_i. \end{cases}$$

C. Estimating Optimal PIT size

In order to estimate the optimal size of the PIT at the routers, we first solve for the stationary probability vector $\boldsymbol{\pi}$ using the discussions in Sections III-A and III-B. Depending on the input process, every element of $\boldsymbol{\pi}$ can in turn be a vector. In general, the PIT does not have any extra buffer available, i.e., $K = 0$. Therefore, our queue model becomes a $GI/M/c/c$ queue. When the PIT is in state c, it implies that the PIT is full and any incoming interests will be dropped. Hence, the drop probability at the PIT is $\boldsymbol{\pi}_c$. Let the maximum desired drop probability be ϵ.

As the cost of PIT is an increasing function of the size of the PIT, the objective of our optimization problem is to minimize the size of PIT c subject to the upper bound ϵ on the drop probability $\boldsymbol{\pi}_c$.

We formally describe the optimization problem as

$$\begin{aligned} \text{minimize} \quad & c \\ \text{subject to} \quad & \boldsymbol{\pi}_c^T \boldsymbol{e} \ < \ \epsilon, \\ & c \in \mathbb{N} \end{aligned} \tag{20}$$

where $\boldsymbol{e} = (1, 1, \cdots, 1)^T$ is a column vector of length $|\boldsymbol{\pi}_c|$.

The optimal PIT size needs to be evaluated for resource planning of the network during the initial deployment. Since this is not a real-time optimization scenario, we do not require a very fast approach to solve the optimization problem.

We implement the exponential search (a of variant bisection method) in Matlab to solve the optimization problem. As the drop probability is a decreasing function of c, we initialize c to be a lower bound (e.g., $c = 1$) and then use exponential search to find the optimal value of c which satisfies the drop probability constraint. As $c \in \mathcal{N}$, the time complexity of this algorithm is $O(T \log c)$, where T is the time complexity of evaluating the drop probability $\boldsymbol{\pi}$ for a given c. The time complexity of matrix multiplication and matrix inversion is $O(N^{2.373})$, therefore $T \in O(N^{3.373})$.

D. Estimation of mean service time

In this section we characterize the average service time $(1/\mu)$ in detail and derive a closed form expression for the same. Our discussion accounts for the caching at the content stores of the routers as well as for the mobility of producers. The following discussion holds for stationary producers as well. The service time for an interest in the PIT depends on several variables like the transmission rate at the (upstream) routers, the propagation delay between the routers, the processing delay at the routers, the cache hit rate for the interest at the routers, and the load at the content producer. A complex general service time distribution is required to accommodate all these variables. For computational tractability, we consider that the service time is exponentially distributed and evaluate the mean service time while accommodating the above mentioned variables. In the existing literature, authors of [15], [17], [18], [22] have similarly considered the service time to be exponentially distributed for the interests.

The round trip time (RTT) between the consumer and node i is denoted by $t(i)$. We can estimate $t(i)$ as follows:

$$t(i) = \sum_{j=1}^{i-1} \left(\frac{D}{B_j^{j+1}} + 2R_j^{j+1} \right).$$

Here, D is the size of the data chunk, B_i^j is the bandwidth of the link between nodes i and j, and R_i^j is the propagation delay between nodes i and j. The size of interests is orders of magnitude smaller than the typical data packets (i.e.,content). Hence, transmission time of the interest is negligible when compared to the propagation and transmission time of the content and is thus ignored. We note that the interest transmission time can be easily accounted for by replacing D with $D + I$ where I is the size of the interest.

1) Caching at content stores: Now, we model the ICN's caching at content stores of the routers and in order to do so, we need to estimate the cache miss probabilities at the intermediate nodes along the path of requests. As the cache hits depend on the popularity of the content, let the content belong to an arbitrary content popularity class κ. Let $m_\kappa(i)$ be the cache miss probability of the content at the intermediate node i. Under the assumption that all caches implement the Least Recently Used (LRU) cache replacement policy, $m_\kappa(i)$ is evaluated by the following expression [23]:

$$\begin{aligned} \log m_\kappa(i) &= \prod_{j=1}^{i-1} \left(\frac{C_{j+1}}{C_j} \right)^z \ m_\kappa(j) \log m_\kappa(1), \quad \forall\ i > 1, \\ m_\kappa(1) &= \exp\left(- \left(\frac{C_1}{S_\kappa \kappa \sigma \Gamma(1 - \frac{1}{z})} \right)^z \right). \end{aligned} \tag{21}$$

Here, C_i is the cache size of the i^{th} router (from the consumer), S_κ is the number of contents in the class κ, σ is the average size of the contents and z is the Zipf's constant. The intuition behind Equation (21) is briefly described in Appendix A. For simplicity, we consider an arbitrary content class and omit the class index κ.

Next, we consider the impact of producer's movement using the following two scenarios.

2) Before hand-off: The average service time in this case is evaluated as a weighted sum of the round trip time (RTT) between the consumer and every intermediate node. Here, the weights are the probability of finding the data at the corresponding intermediate nodes. For the data to be served by the i^{th} node, the data should not be present in the cache of the previous $(i-1)$ nodes and it should be present in the cache of the i^{th} node. Let $f(i)$ denote the probability of this event to occur. Then $f(i)$ is evaluated as:

$$f(i) = (1 - m(i)) \prod_{j=1}^{j=i-1} m(j).$$

Let the producer be the n^{th} node. Then average service time, $T_1(n)$, for this case can be calculated as:

$$T_1(n) = \sum_{i=1}^{n} f(i) t(i). \tag{22}$$

The amount of time the producer is connected to a given cellular base station or a Wi-Fi access point (between two consecutive hand-offs) can be modeled as a generalized Gamma distribution [24]. We denote the expectation of this time by u_1. Then, u_1 is evaluated as follows:

$$u_1 = \frac{\pi R}{2v}.$$

Here, every cell is assumed to be a circle, R is the cell radius, and v is the average speed of the producer. Readers can refer to [24] for more details.

3) After hand-off occurs: Now, consider the scenario where the data is not cached at any of the intermediate nodes and a producer hand-off has also occurred (hence, the producer is not reachable). Let us denote the path to the producer before the hand-off by l and the new path after the hand-off by $\hat{l}$. This information about the hand-off (and the new path) has to be propagated to all the nodes in the network and the respective Routing Information Bases (RIBs) and the FIBs need to be updated. There are a few approaches proposed in the literature for the same [6], [7], [25]. Let u_2 denote the average time taken by the chosen approach to update all the (relevant) nodes. This implies that once the hand-off occurs, the producer is not reachable for time u_2 (although the interests can still be served if the requested data is present in any of the caches along l). The average service time in this case is given by

$$T_2 = T_1(n) + u_2 + T_1(\hat{n}), \tag{23}$$

where $\hat{n}$ is the index of the producer along the new path $\hat{l}$.

Let the probability that the producer is reachable at any arbitrary time be denoted by q. Then, we can calculate q as follows:

$$q = \frac{u_1}{u_1 + u_2}.$$

Using Equations (22) and (23), we can estimate the mean service time, $\frac{1}{\mu}$, of our system as follows:

$$\begin{aligned}\frac{1}{\mu} &= qT_1(n) + (1-q)T_2 \\ &= T_1(n) + (1-q)(u_2 + T_1(\hat{n})).\end{aligned}$$

The value of u_2 depends on the approach used for updation. For example, u_2 for the approach in [25] can be considered to be a constant whereas modeling u_2 is more complex for approaches like [6], [7] as they involve the retransmission of interests. We note that this analysis also holds for stationary producers by setting the value of $u_2 = 0$.

E. Sojourn time distribution

The $GI/M/c/N$ queue model discussed in Section III-A can also be used to characterize the consumer. Here, c denotes the number of pending interests requested by the consumer and K denotes the interest buffer at the consumer ($N = c + K$). The arrival process and the service time distribution are the same as the case of PIT. The distribution of sojourn time is of interest to us as it can be used for estimating parameters like interest timeout. An arriving interest is subject to one of the following two mutually exclusive events. First, the arriving interest is not required to be buffered (queued) and is forwarded immediately (no waiting time). Second, there are c pending interests and hence the arriving interest is buffered. Let $S(t)$ be the CDF of the sojourn time. Then,

$$S(t) = \sum_{k=0}^{c-1} \pi_k F(t) + \sum_{k=c}^{N} \pi_k (G_k * F)(t). \tag{24}$$

Here, π_k is the probability of consumer being in state k, and $F(t)$ and $G_k(t)$ are the CDFs of the service and the waiting time when the state is k, respectively. As the queue is modeled as a $GI/M/c/N$ queue, $F(t)$ and $G(t)$ follow the exponential and the Erlang distributions, respectively, and are given by

$$\begin{aligned} F(t) &= 1 - \mu e^{-\mu t} \qquad (25)\\ G_k(t) &= 1 - \sum_{j=0}^{k-c} \frac{(c\mu t)^j e^{-c\mu t}}{j!}.\end{aligned}$$

Let $H_k(t) = (G_k * F)(t)$. Then $H_k(t)$ is evaluated as follows:

$$\begin{aligned} H_k(t) &= \int_0^t \left(1 - \sum_{j=0}^{k-c} \frac{(c\mu y)^j e^{-c\mu y}}{j!}\right) \mu e^{-\mu(t-y)} dy \\ &= \int_0^t \mu e^{-\mu(t-y)} dy \\ &\quad - \sum_{j=0}^{k-c} \frac{(c\mu)^j \mu e^{-\mu t}}{j!} \int_0^t y^j e^{(-(c-1)\mu y)} dy \\ &= (1 - e^{-\mu t}) - \sum_{j=0}^{k-c} \frac{(c\mu)^j \mu e^{-\mu t}}{((c-1)\mu)^{j+1}}. \\ &\qquad \int_0^t ((c-1)\mu)^{j+1} \frac{y^j e^{-(c-1)\mu y}}{j!} dy \\ &= (1 - e^{-\mu t}) - \sum_{j=0}^{k-c} \frac{(c\mu)^j \mu e^{-\mu t}}{((c-1)\mu)^{j+1}}. \\ &\qquad \left(1 - \sum_{i=0}^{j} \frac{((c-1)\mu t)^i}{i!} e^{-(c-1)\mu t}\right). \end{aligned} \tag{26}$$

Using Equations (24), (25) and (26), we get

$$\begin{aligned} S(t) &= \sum_{k=0}^{c-1} \pi_k (1 - \mu e^{-\mu t}) + \\ &\quad \sum_{k=c}^{N} \pi_k \left[(1 - e^{-\mu t}) - \sum_{j=0}^{k-c} \frac{(c\mu)^j \mu e^{-\mu t}}{((c-1)\mu)^j + 1} \right. . \\ &\quad \left. \left(1 - \sum_{i=0}^{j} \frac{((c-1)\mu t)^i}{i!} e^{-(c-1)\mu t}\right)\right]. \end{aligned} \tag{27}$$

F. Parameter Esitimation

The various parameters required to solve the optimization problem can be obtained as follows. The interest arrival rate λ, link bandwidth B, the size of the data packet D, the link propagation delay R, and the average content size σ can be observed by the router. The cache size of the router is a

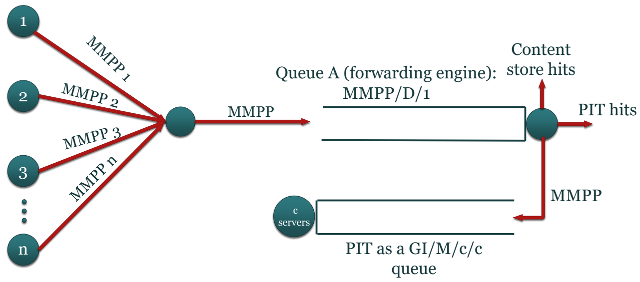


Fig. 2. Traffic flow in a router

known constant. The average arrival rate can be observed over a period of time by the router (or historical data can be used) to classify the contents into different popularity classes and determine the Zipf's constant z, and the number of contents in content class S.

IV. Input Process

The $GI/M/c/N$ queue discussed in the previous sections considers a general arrival process. For the purpose of our simulations we assume that the consumers generate interests using the Markov Modulated Poisson Process which is a doubly stochastic process. MMPP is widely used in models of communication systems as it is capable of capturing the correlations of inter-arrival times and qualitatively representing the time dependent arrival rates while still remaining computationally tractable. We briefly describe the MMPP and a few of its properties. The MMPP is defined by two parameters $\{Q, \boldsymbol{\lambda}\}$. Q is the infinitesimal generator of the underlying m-state continuous time Markov chain and $\boldsymbol{\lambda}$ is the Poisson arrival rates corresponding to the m states. Formally, we define the following:

$$Q = \begin{bmatrix} -\sigma_1 & \sigma_{12} & \cdots & \sigma_{1m} \\ \sigma_{21} & -\sigma_2 & \cdots & \sigma_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{m1} & \sigma_{m2} & \cdots & -\sigma_m \end{bmatrix}$$

$$\sigma_i = \sum_{\substack{j=1 \\ j\neq i}}^{m} \sigma_{ij}$$

$$\boldsymbol{\lambda} = (\lambda_1, \lambda_2, \cdots, \lambda_m)^{\mathrm{T}}$$

$$\Lambda = \mathrm{diag}(\boldsymbol{\lambda}^{\mathrm{T}}).$$

Property 1. : The superposition of n MMPPs $\{Q_1, \Lambda_1\}$, $\{Q_2, \Lambda_2\}$, $\cdots$, $\{Q_n, \Lambda_n\}$ is an MMPP defined by $\{Q, \Lambda\}$ as follows

$$Q = Q_1 \oplus Q_2 \oplus \cdots \oplus Q_n,$$
$$\Lambda = \Lambda_1 \oplus \Lambda_2 \oplus \cdots \oplus \Lambda_n,$$

where $\oplus$ represents the Kronecker-sum (defined in [26]). If Q_i and Λ_i are $k_i \times k_i$ matrices, then Q and Λ are $k \times k$ matrices such that $k = \prod_{i=1}^{n} k_i$.

Proof. Refer to [27]. □

Let us consider the traffic flow in an arbitrary router R as depicted in Figure 2. The incoming interests first enter the forwarding engine (queue A), where the forwarding decision is made. If a content store (CS) hit occurs, the data is responded back to the corresponding faces. If a PIT hit occurs, the corresponding entry in the PIT is updated. In the case where a miss occurs at both CS and PIT, the interest is forwarded to the appropriate face and an entry is created in the PIT. Let all the input processes at R be MMPPs. Then, from Property 1, the resultant input process to R is an MMPP, $\{Q, \Lambda\}$.

Parameter	Value
Network topologies	Exodus, Abovenet, and Tiscali
Backbone to backbone link (bandwidth, propagation delay)	1 Gbps, 20 ms
Backbone to gateway link (bandwidth, propagation delay)	0.5 Gbps, 10 ms
gateway to access router link (bandwidth, propagation delay)	0.1 Gbps, 5ms
Content classes	5
Zipf's constant	2
Mean arrival rate of the content classes	20, 9, 5, 3, 2
Number of contents	2000 in each class
Number of consumers	50
Number of producers	3
Content store (cache) size	1 % of content universe
Data Chunk size	1024 B

TABLE II
SIMULATION PARAMETERS

We assume that the service capacity of queue A is very large when compared to the interest traffic intensity ($\mu >> \lambda$). To justify this assumption, we note that the size and number of interests being handled by a router at any time (generally) is orders of magnitude smaller that the data packets (i.e., content). Existing literature on routing table lookup show that lookups can be performed in constant time [28], [29]. Hence, we assume that the time required by a router to make the forwarding decision to be a constant, h. Under the given assumptions, queue A is a MMPP/D/1 queue with negligible waiting time.

Property 2. The output process of an MMPP/D/1 queue with $\mu >> \lambda$ can be approximated as a translation of the input MMPP.

Proof. See Appendix B. □

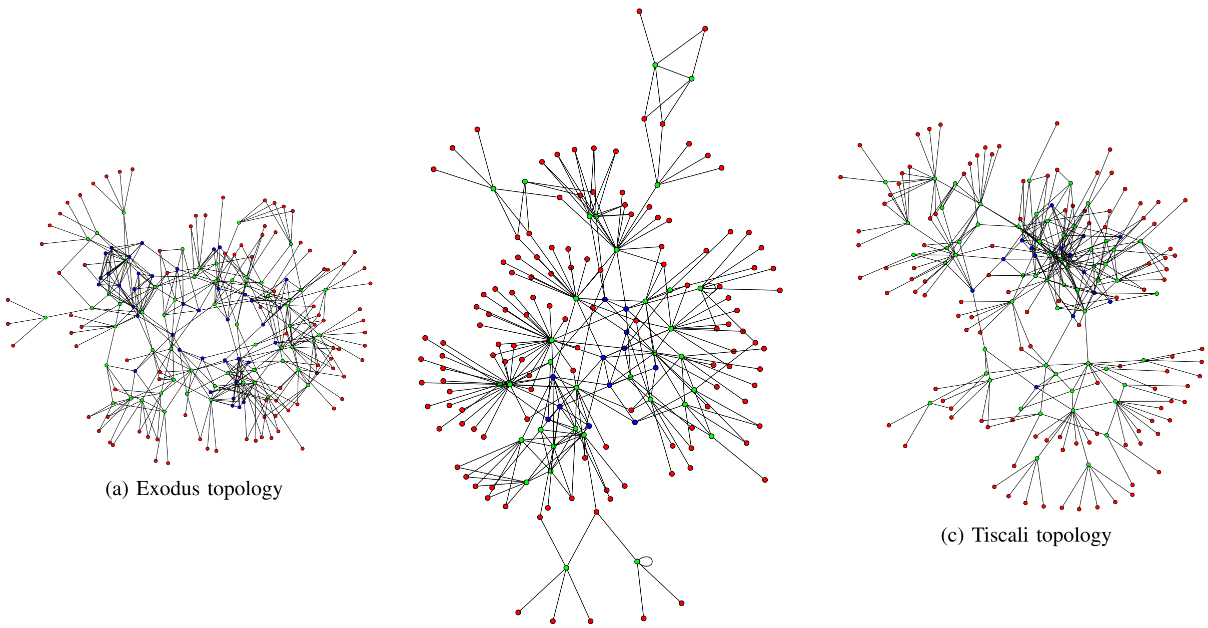
Remark 1. Our model can easily accommodate cases with CS and PIT hits. Let p and q be the average hit rates for CS and PIT and let the input MMPP for the router be defined by $\{Q, \bar{\Lambda}\}$. Then the adjusted arrival rate Λ can be evaluated as

$$\Lambda = (1-p)(1-q)\bar{\Lambda}.$$

When MMPPs are superposed the state space of the resultant MMPP grows exponentially. Hence we approximate the m state MMPP (the resulting arrival process at the router) with a 2 state MMPP using the following property (Property 3).

Property 3. An m-state MMPP can be approximated by a 2-state MMPP by matching the first three non-central moments.

Proof. We refer the readers to [30] for the proof and the accuracy of the property. We briefly describe the approximation methodology in Appendix C. □



(a) Exodus topology

(b) Abovenet topology

(c) Tiscali topology

Fig. 3. Rocketfuel topologies used in the simulations. The blue, green and red nodes are backbone, gateway, and access routers, respectively.

V. Simulation Results

In this section, we validate our analytical model and assumptions using realistic networks. We consider five different content classes and let the mean interest arrival rate be λ_i for content class $i,\ i \in \{1, \cdots, 5\}$. We assume that the content popularity follows the Zipf's law with the Zipf's constant $z = 2$. Each data packet is 1024 bytes. The consumers generate interests according to a two-state MMPP with parameters Q, Λ_i as follows:

$$Q = \begin{bmatrix} -0.1 & 0.1 \\ 0.1 & -0.1 \end{bmatrix}, \quad \Lambda_i = \begin{bmatrix} \lambda_i & 0 \\ 0 & 0 \end{bmatrix}.$$

First, we compare the optimal PIT sizes evaluated by our proposed model and the model proposed in [18] where the authors model the PIT occupancy using a Markov chain (refereed to as 'MC'). Then, to further validate our model, we compare the optimal PIT sizes and the drop probabilities estimated by our analytical model and that achieved from the simulations across various system parameters.

We adopt three different network topologies obtained from Rocketfuel network topology traces for ISP Exodus, Abovenet and Tiscali (the topologies are shown in Figure 3a, 3b and 3c). We refer to the topologies as EX, AB and TI in our results. We suffix the names with M and S to indicate the results obtained from our analytical model and simulations, respectively. In every topology, there are 50 consumers connected to the edge routers and three producers connected to one of the back bone routers. The link capacities and delays are set as follows. The backbone-to-backbone links have a capacity of 1 Gbps and a propagation delay of 20 ms. The backbone-to-gateway and gateway-to-gateway links have a capacity of 0.5 Gbps and a propagation delay of 10 ms. The gateway to access router links have a capacity of 0.1 Gbps and a propagation delay of 5 ms. We use the NS-3 based ndnSIM simulator [31]. For all the simulation scenarios mentioned, we run the simulations 100 times and present our findings which are averaged over all the simulation runs. The simulation parameters are summarized in Table II.

A. Comparison with MC model

In this section, we compare the optimal PIT sizes evaluated by our proposed model and the MC model. We vary the value of ϵ as 0.2, 0.1, 0.05, 0.01, and 0.001. Using both the models, we evaluate the optimal PIT size of the bottleneck router. The PIT size of other routers in the network are set such that they do not become the bottleneck. The obtained optimal PIT sizes for topologies EX, AB and TI are depicted in Figure 4, Figure 5 and Figure 6, respectively. We observe that MC overestimates the optimal PIT size for smaller values of ϵ. For example, in case of EX topology with $\epsilon = 0.01$, the optimal PIT size obtained from MC, our proposed model and simulations are 80, 53 and 54, respectively. The overestimation would increase the cost of the PIT. We also observe that for larger values of ϵ, MC underestimates the optimal PIT size. For example, in case of AB topology with $\epsilon = 0.1$, the optimal PIT size obtained from MC, our proposed model and simulations are 34, 34 and 20, respectively. This would result in more interest drops than expected.

B. Effect of ϵ

In this section we study the effect of ϵ on the optimal PIT size and the drop probabilities. We vary the value of ϵ as 0.2, 0.1, 0.05, 0.01, and 0.001. For this scenario, we evaluate our analytical model to estimate the optimal PIT size of the bottleneck router of the networks. The PIT size of other routers in the network are set such that they do not become the bottleneck. The obtained optimal PIT size and

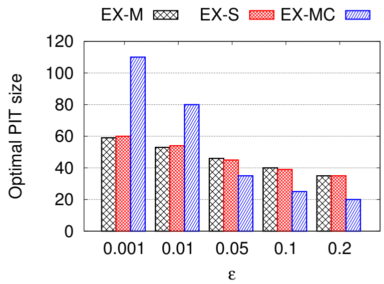


Fig. 4. Optimal PIT sizes: EX topology

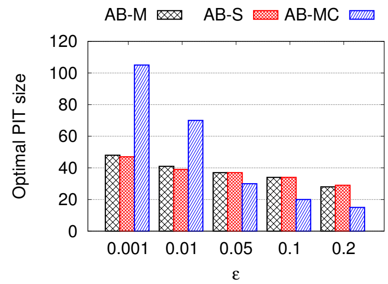


Fig. 5. Optimal PIT sizes: AB topology

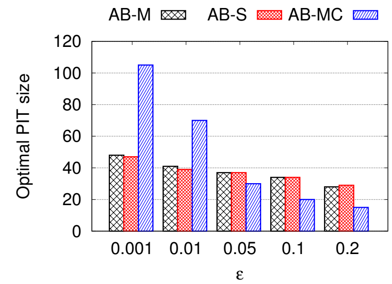


Fig. 6. Optimal PIT sizes: TI topology

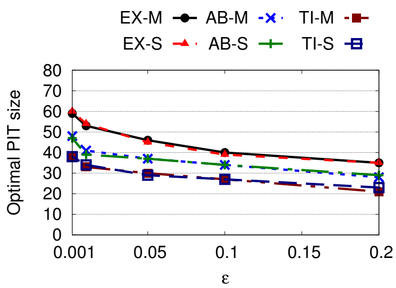


Fig. 7. Effect of ϵ on optimal PIT size.

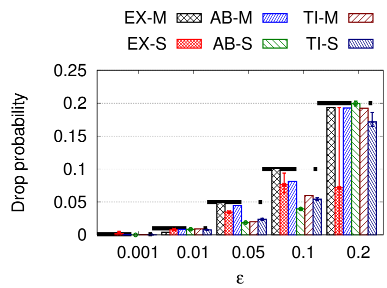


Fig. 8. Effect of ϵ on drop probability. The horizontal bars denote the value of ϵ.

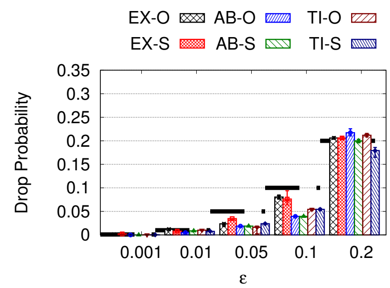


Fig. 9. Drop probabilities obtained using analytical optimal PIT size and simulation optimal PIT size. The horizontal bars denote the value of ϵ.

drop probabilities are depicted in Figure 7 and Figure 8. We can observe that the optimal PIT size increases as the value of ϵ decreases for all the networks. For instance, in the case of AB, the optimal PIT size increases as 34, 37 and 48 as the value of ϵ decreases as 0.1, 0.05 and 0.001, respectively. We also note that the drop probabilities achieved by simulations respect the constraint (ϵ) posed by our analytical model. For example, in the case of EX the simulation drop probabilities achieved are 0.08, 0.035 and 0.008 for the ϵ values 0.1, 0.05, 0.01, respectively. In order to investigate the effect of modeling the service time as an exponential distribution, we perform network simulations using the optimal PIT size obtained using our analytical model (from Figure 7) and compare them with the simulation drop probabilities (from Figure 8). Note that the simulation results are based on the exact service time experienced by the interests. The drop probabilities are depicted in Figure 9. Here, the suffix 'O' represents the drop probabilities obtained while using the theoretical values of optimal PIT size. We observe that there is a close match between the drop probabilities which validates our simplification of the service time to follow an exponential distribution. For example, in the case of AB, when ϵ decreases as 0.2, 0.1, and 0.01, the drop probabilities from theoretical values of optimal PIT size are 0.21, 0.039, and 0.005, respectively, whereas the drop probabilities from simulation values of optimal PIT size are 0.199, 0.039, and 0.008, respectively.

C. *Effect of Demand*

In this section we study the effect of varying demand on the optimal PIT size and the drop probabilities. We vary the value of λ_i with multiplicative factors of 0.75, 1, 1.25, 1.5, 1.75, and 2. The value of ϵ is set to 0.01 for all the cases. As in the previous scenario, we evaluate our model to estimate the optimal PIT size of the bottleneck router. The obtained optimal PIT size and drop probabilities are shown in Figure 10 and Figure 11, respectively. The optimal PIT size increases with the increasing demand for all the networks. For example, the optimal PIT size in case of EX increases as 53, 72 and 89 for the demand of 0.75, 1.25 and 2, respectively. Also, as the value of ϵ is set to 0.01, we expect the drop probabilities to be less that 0.01. For instance, in case of EX the simulation drop probabilities of 0.008, 0.003 and 0.009 are achieved for the demand of 1, 1.5 and 2, respectively.

D. *PITs in tandem*

In this section, we study how our model performs while considering multiple routers in tandem. Using our model we estimate the optimal PIT sizes for the five most significant routers in every topology. The value of ϵ is set to 0.01 for all the routers in all the topologies. We depict the results obtained in Figure 12 and Figure 13. In general, we observe that the simulations closely follow the estimations of our analytical model. For example, the optimal PIT size estimated by our model for the routers of TI are 21, 21, 19, 19, 33 and the optimum PIT sizes achieved in simulations are 21, 20, 18, 18, 34 respectively. The simulation drop probabilities achieved with these PIT sizes are 0.007, 0.002, 0, 0.001, 0.001, respectively, and hence respect the constraint on the drop probabilities.

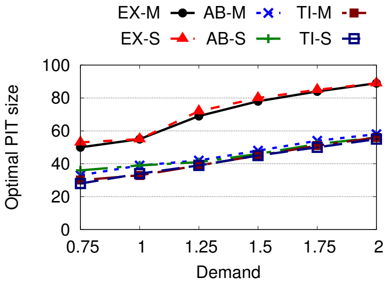


Fig. 10. Effect of demand on optimal PIT size.

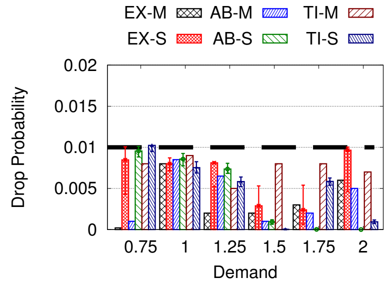


Fig. 11. Effect of demand on drop probability. The horizontal bars denote the value of ϵ.

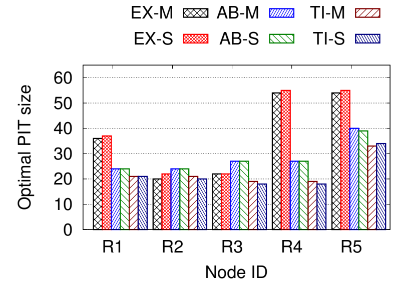


Fig. 12. Optimal PIT size with Tandem PITs.

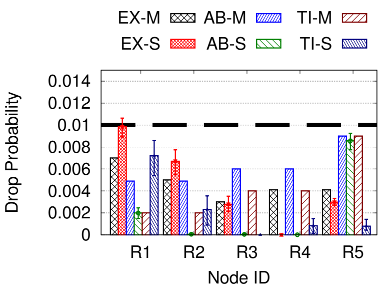


Fig. 13. Drop probability with Tandem PITs. The horizontal bars denote the value of ϵ.

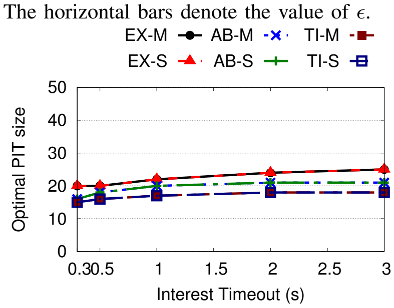


Fig. 14. Effect of α on optimal PIT size.

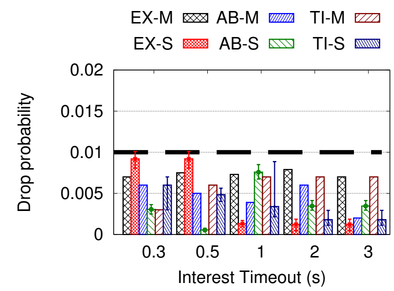


Fig. 15. Effect of α on drop probability. The horizontal bars denote the value of ϵ.

E. Effect of α

In this section, we evaluate the model with interest timeouts presented in Section III-B. For every topology, we consider one of the access routers (with maximum traffic) directly connected to consumers in this scenario. We vary the value of α by varying the interest lifetime as 0.3, 0.5, 1, 2, and 3 seconds and solve the optimization problem presented in Equation (20) for the access router to estimate its optimal PIT size. The value of ϵ is set as 0.01. The obtained optimal PIT sizes and drop probabilities are shown in Figure 14 and Figure 15, respectively. We observe that as the value of α increases the optimal PIT size increases. This is expected as increasing the value of α implies an increase in the lifetime of interests and hence an increase in the number of outstanding interests at the routers. For instance, the optimal PIT size for EX varies as 20, 22, 24 as α increases as 0.5 s, 1 s, 2 s and the simulation drop probabilities achieved are 0.009, 0.002, 0.002, respectively.

F. Effect on Content Store

Now we report the effect of our model on the content store of the routers. We consider the scenario as mentioned in Section V-B for all the topologies. The content store size of all the routers is set to 1% of total content universe. We vary the values of ϵ as 0.2, 0.1, 0.05, 0.01, and 0.001 and depict the obtained hit rates at the content store in Figure 16. In general, we observe that the hit ratio does not vary significantly with the value of ϵ. For example, the hit ratios achieved for AB are 1.04%, 1.02%, 1.01%, 0.8% for the ϵ values of 0.1, 0.05, 0.01, 0.001, respectively. As the content store size is 1% and achieved hit ratio is 1% irrespective of the value of ϵ, we observe that the content store hit ratio is independent of the value of ϵ.

G. Effect of c on Drop probability

In this section we study the effect of c on the drop probabilities. For this scenario, we evaluate our analytical model to estimate the drop probability at the bottleneck router of the networks. The PIT size of other routers in the network are set such that they do not become the bottleneck. The obtained drop probabilities are depicted in Figure 17. We can observe that for all the topologies, the drop probability decreases as c increases. We also note that for EX and AB topologies, our model slightly over-estimates the drop probabilities when compared to the simulations. For example, in case of EX with $c = 46$ the drop probabilities obtained by the analytical model and the simulations are 0.048 and 0.035, respectively.

H. Sojourn time

In this section, we evaluate the sojourn time estimation denoted in Equation (24) by applying our model to the consumers. The traffic model at the consumers is the same as discussed in the previous scenarios. In addition, the consumers have a maximum of 10 pending interests ($c = 10$) and an extra buffer of 10 interests ($k = 10$). The consumer is assumed to be stationary. We consider real life mobility traces to model the producer mobility (to evaluate our service time model in Equation (32)). The traces are obtained from [32] where a 8000 m $\times$ 8000 m area in the center of Rome is considered and the GPS co-ordinates of 370 taxis (in the specified area) are captured. We use the GPS co-ordinates and the timestamps from this trace to simulate the movement of the producer. We assume that the concerned area is well connected by cellular base stations with an average transmission range of 2000 m. The consumer and the producer are connected to the cellular base stations. While there are many approaches to update the network about the movement of producers [6], [7], [25], we

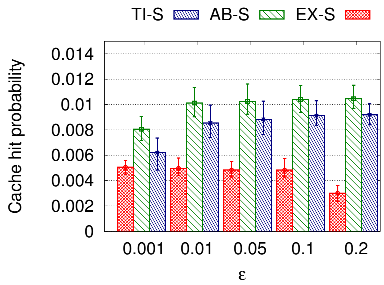


Fig. 16. Effect of ϵ on content store hit.

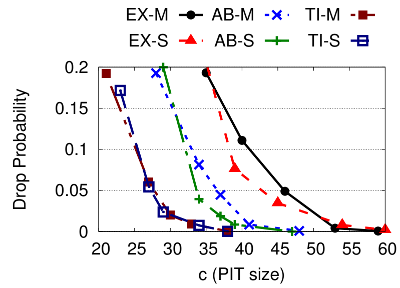


Fig. 17. Drop probability as a function of c.

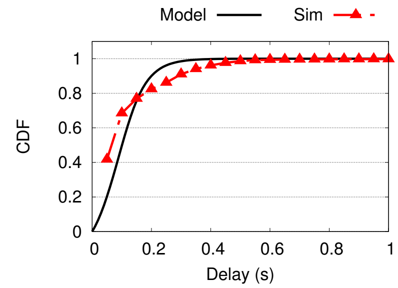


Fig. 18. Sojourn time distribution.

use the approach mentioned in [7] in this paper. We model the value of u_2 according to this approach (Appendix D). We plot the obtained results in the Figure 18 and we note that the delay obtained from the simulations closely follow the estimations of our model. We can note that 40% of the traffic has a low delay of 0.1 s which can be attributed to the in-network caching at the content stores of the routers. The remaining traffic experience a delay between 0.1 s and 0.4 s which accounts for the producer mobility and the delay incurred due to the hand-off.

We note that the drop probabilities obtained by solving our analytical model and the simulations, while close, are not an exact match. This is because we assume the service time distribution to be exponentially distributed in our analytical model (for analytical tractability) whereas the behavior of the network is not exactly the same. Inter-arrival time and the remaining service time play a major role in determining the performance of the system (in terms of drop probability). Let ν_i be the remaining service time of the i^{th} active server. Then the condition for an interest to be dropped is $\min_{1\leq i\leq c} \nu_i > \frac{1}{\lambda}$, i.e., all the servers are active and the minimum of the remaining service times (of the c servers) is greater than average inter-arrival time. In case of the analytical model, the service time is exponentially distributed and hence, the remaining service time is also exponentially distributed with the same mean [19]. However, in real life (and in the simulations) the service time depends on various factors like the transmission delays at the routers, propagation delays between the routers, cache hits at the routers, and the processing delay at the producer. Hence, the distribution of the service time is not exponential (or something that can be modeled using standard distributions). The approximation of exponential service time for analytical tractability in the model thus leads to the differences in the drop probabilities. In case the service time is exponential, our model predicts drop probabilities that match very closely with the simulations. To demonstrate this, we compare the system state probabilities obtained by our analytical model and a discrete event simulation (performed using Matlab) of a $GI/M/c/N$ queue. Here, we set $\lambda = 45$, $\mu = 10$, and $K = 0$. We vary the value of c as 5, 7, and 10. The obtained probabilities are depicted in Figure 19. As the service distribution used in these simulations is exponentially distributed, we observe a very close match between the system state probabilities obtained from our analytical model and the discrete event simulation.

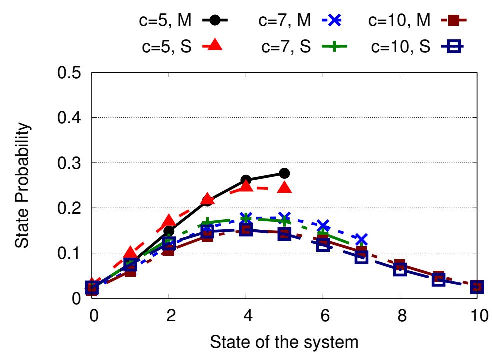


Fig. 19. Drop probability as a function of c.

VI. Conclusion

In this paper, we have modeled the PIT of a router using a $GI/M/c/N$ queue. Using this model we have evaluated the optimal size of the PIT to trade-off between the cost of the PIT and the network performance (in terms of the PIT drop probability). To this end, we have formulated an optimization problem with the objective of minimizing the PIT size while subjecting the interest drop probability to an upper bound. We have also used the developed model to characterize the content delivery time for the consumers. We have demonstrated the accuracy of our analytical model using simulations on different Internet Service Provider topologies across a wide range of system parameters.

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APPENDIX

A. Cache Miss Rate

Che's approximation for an LRU cache of size C [33] evaluates the cache miss rate for an object n as follows

$$f(n) = e^{-q(n)t_c},$$

where t_c is the unique root for the equation

$$\sum_{n=1}^{N}(1 - e^{-q(n)t}) = C.$$

This approximation assumes unitary content size. This result has been extended in [23] assuming that the popularity follows Zipf's law and non-unitary content size. Let z be the Zipf's constant. The cache miss for a content at the first router can be derived using Che's approximation. Let the content belong to an arbitrary popularity class κ, S be the number of contents in each class, σ be the average content size, and C_1 be the size of cache of the first router. Then the cache miss is given by

$$m_\kappa(1) = \exp\left(-\left(\frac{C_1}{S\kappa\sigma\Gamma(1-\frac{1}{z})}\right)^z\right).$$

Let us consider the j^{th} and $(j+1)^{\text{th}}$ routers along the path from the consumer to the producer. The requests arriving at $(j+1)^{\text{th}}$ router are the requests that have a cache miss at all the previous j routers. Hence, the cache miss rate at $(j+1)^{\text{th}}$ router recursively depends on the cache miss rate of $1^{\text{st}}, \cdots, j^{\text{th}}$ routers. Evaluating this relation gives

$$\log m_\kappa(i) = \prod_{j=1}^{i-1}\left(\frac{C_{j+1}}{C_j}\right)^z \; m_\kappa(j)\log m_\kappa(1), \quad \forall\; i > 1.$$

B. Proof for Property 2

MMPP/D/1 queue is a special case of N/G/1 queue. The LST of inter-departure times for a N/G/1 queue [34] is as follows:

$$D(s) = H(s)\left(\sum_{k=1}^{N}\boldsymbol{x}_k\boldsymbol{e} + \boldsymbol{x}_0(sI - R(0))^{-1}(R(1) - R(0))\boldsymbol{e}\right). \tag{28}$$

Here, N is the capacity of the system, $\boldsymbol{x}_i$ is the probability of the system being in state i, $H(s)$ is the LST of the service time, and for the detailed definition of $R(z)$ we refer the readers to [34]. Under low traffic intensity with high service capacity (i.e. $\mu >> \lambda$), the departing request will leave an empty system behind for most of the time, i.e., $\boldsymbol{x}_k\boldsymbol{e} \approx 0,\ \forall i \geq 1$. Hence, the Equation (28) reduces to

$$D(s) = H(s)\left(\boldsymbol{x}_0(sI - R(0))^{-1}(R(1) - R(0))\boldsymbol{e}\right). \tag{29}$$

For the MMPP/D/1 queue, $R(0)$, $R(1)$ and $H(s)$ are defined as follows [34]:

$$R(0) = Q - \Lambda \tag{30}$$
$$R(1) = Q \tag{31}$$
$$H(s) = e^{-sh}, \tag{32}$$

where h is the mean service time. Hence, using Equations (29), (30), (31) and (32) we can evaluate the LST of inter-departure times for an MMPP/D/1 queue with negligible waiting times as follows:

$$D(s) = \boldsymbol{x}_0 e^{-sh}(sI - Q + \Lambda)^{-1}\Lambda\boldsymbol{e}. \tag{33}$$

The LST of inter-arrival times for an MMPP process is given as

$$F(s) = (sI - Q + \Lambda)^{-1}\Lambda. \tag{34}$$

From Equations (33) and (34), we can observe that the inter-departure times are a convolution of inter-arrival times with the constant service time distribution, i.e., the output process is a translation of the input process. Hence, the output process is also an MMPP.

C. Approximation methodology for property 3

The i^{th} non-central moment of the arrival rate of the MMPP $\{Q, \Lambda\}$ is given as

$$\alpha_i = \boldsymbol{\pi}\Lambda^i\mathbf{e},$$

where $\boldsymbol{\pi}$ is the steady state probability vector of the underlying Markov chain of MMPP.

The covariance function is given by

$$r(t) = \boldsymbol{\pi}\Lambda(\mathrm{e}^{Qt} - \mathbf{e}\boldsymbol{\pi})\Lambda\mathbf{e}.$$

and the time constant is calculated as

$$\begin{aligned}\tau &= \nu^{-1}\int_0^{\infty} r(t)dt \\ &= \nu[\boldsymbol{\pi}\Lambda(\mathbf{e}\boldsymbol{\pi} - Q)^{-1}\Lambda\mathbf{e} - m^2],\end{aligned}$$

where ν and m are the variance and mean of the arrival rate process.

Let the two state MMPP be given as

$$\hat{Q} = \begin{bmatrix} -r_1 & r_1 \\ r_2 & -r_2 \end{bmatrix} \quad \hat{\Lambda} = \begin{bmatrix} -\hat{\lambda}_1 & 0 \\ 0 & -\hat{\lambda}_2 \end{bmatrix}.$$

Computing the first three moments and the time constant for the 2 state MMPP we get,
$\alpha_1 = \hat{\lambda}_2\hat{\pi}_1 + \hat{\lambda}_2\hat{\pi}_2$; $\alpha_2 = \hat{\lambda}_1^2\hat{\pi}_1 + \hat{\lambda}_2^2\hat{\pi}_2$; $\alpha_3 = \hat{\lambda}_1^3\hat{\pi}_1 + \hat{\lambda}_2^3\hat{\pi}_2$; $\tau = (r_1 + r_2)^{-1}$; $\hat{\pi}_1 = \frac{r_2}{r_1+r_2}$.

As the 2 state MMPP is an Interrupted Poisson process, $\hat{\lambda_2} = 0$ and solving the equations we get,
$\hat{\lambda_1} = \frac{\alpha_2}{\alpha_1}$, $r_2 = \tau^{-1}\frac{\alpha_1^2}{\alpha_2}$, $r_1 = \tau^{-1}\frac{\alpha_2 - \alpha_1^2}{\alpha_2}$.

D. Estimation of u_2

We model the value of u_2 according to the approach mentioned in [7]. Let S the random variable denoting the number of attempts/retransmissions required to locate the producer. We denote the time between $(i-1)^{\text{th}}$ and i^{th} retransmission as an i.i.d. random variable T_i with a probability generating function $G_T(z)$. Let p be the success probability of every retransmission. The event of successfully locating the producer follows a geometric distribution. Hence, the probability of locating the producer in n^{th} retransmission is given by

$$P(S = n) = p(1-p)^{n-1}$$

Let the total updation time be denoted by random variable R. Then, R is evaluated as follows

$$R = \sum_{i=1}^{S} T_i$$

and its probability generating function $H(z)$ is given by

$$H(z) = E[z^R] = E[z^{\sum_{i=1}^{S} T_i}]. \tag{35}$$

By conditioning the Equation (35) on the value of n we get

$$\begin{aligned}H(z) &= E\left[\sum_{n=1}^{\infty} z^{\sum_{i=1}^{S} T_i} P(S = n)\right] \\ &= \sum_{n=1}^{\infty} p(1-p)^{n-1}[G_T(z)]^n \\ &= pG_T(z)\sum_{n=1}^{\infty}[(1-p)G_T(z)]^{n-1} \\ &= \frac{pG_T(z)}{1-(1-p)G_T(z)}.\end{aligned} \tag{36}$$

Using the Equation (36), we evaluate the mean updation time u_2 follows

$$u_2 = \frac{\partial H(z)}{\partial z} = \frac{pG_T'(z)}{(1-(1-p)G_T(z))^2}$$

Sivaraman Vignesh received the B.Tech. degree in computer science and engineering from National Institute of Technology, Tiruchirappalli India, in 2014, the M.Tech. degree in computer science and engineering from the Indian Institute of Technology, Guwahati, India, in 2016, He is currently a doctoral student in the department of Electrical and Computer Engineering at National University of Singapore (NUS), Singapore. His research interests include Information Centric Networks, privacy in networks and data center networks.

Dibyajyoti Guha Dibyajyoti Guha received the B. Tech in computer science and engineering from Kalyani Government Engineering College, University of Kalyani, India, in 2003, master of science in telecommunication engineering from the Indian Institute of Technology Kharagpur, India, in 2012, and Ph.D. in Mathematics from the Indian Institute of Technology Bhubaneswar, India, in 2016. He is currently pursuing post doctoral research fellowship in the dept. of Electrical and Computer Engineering, National University of Singapore. He is on lien with department of Information Technology at International Management Institute, Kolkata, India. He has worked in HCL-Cisco Offshore Development Center, Chennai, India and Sipera Systems Inc. (a startup company that was acquired by Avaya in 2011) as a Software Engineer in VoIP/Data/Telecom routing and SSL protocols in Cisco and Juniper high end routers. He has published research papers in premier journals like Performance Evaluation (Elsevier), Information Systems and Operational Research (Taylor and Francis), and Applied Mathematical Modelling (Elsevier). His research interest includes Queueing Theory, Stochastic Analysis of Computer Networks, Machine Learning, Cognitive Science, EEG-based analysis of braincomputer interface.

Biplab Sikdar (S98-M02-SM09) received the B.Tech. degree in electronics and communication engineering from North Eastern Hill University, Shillong, India, in 1996, the M.Tech. degree in electrical engineering from the Indian Institute of Technology, Kanpur, India, in 1998, and the Ph.D. degree in electrical engineering from the Rensselaer Polytechnic Institute, Troy, NY, USA, in 2001. He was on the faculty of Rensselaer Polytechnic Institute from 2001 to 2013, first as an Assistant and then as an Associate Professor. He is currently an Associate Professor with the Department of Electrical and Computer Engineering, National University of Singapore, Singapore. His research interests include computer networks, and security for IoT and cyber physical systems. Dr. Sikdar is a member of Eta Kappa Nu and Tau Beta Pi. He served as an Associate Editor for the IEEE Transactions on Communications from 2007 to 2012 and for the IEEE Transactions on Mobile Computing from 2014-2017.