

Towards Seamless Producer Mobility in Information Centric Vehicular Networks

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Abstract—With the advancement in network infrastructure and the growth of IoT, more and more vehicular systems are getting connected. Architectures like Information Centric Networks (ICN) are being explored for vehicular communication to achieve robust content distribution in highly mobile, dynamic, and error prone domains. Consumer mobility is implicitly supported in ICN while producer mobility is an important challenge. In this paper, we design a mechanism to support producer mobility using the spatial locality of moving producers and reverse paths of data. Then, we model the consumer (requesting) application as a GI/M/c/N queue which is used to estimate system parameters like content delivery time distribution. We perform simulations using real world traces to evaluate the accuracy and working of our model.

I. INTRODUCTION

Efficient distribution and retrieval of content in the current host centric Internet architecture needs different kinds of 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 principal 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]. Such a change can drastically improve content distribution even in highly mobile, dynamic and error prone domains like vehicular ad-hoc networks. When the producer is mobile, the route to the producer changes with time and hence a mechanism is needed to update the other nodes about the producer’s movement. Thus, the effectiveness of the mechanism to support mobility plays a significant part in the overall network performance experienced by the users. To this end, the main objectives of this paper are:

- We develop a robust mechanism to support micro mobility of producers in vehicular ICN leveraging the spatial locality of producers.
- We model the consumer application using a GI/M/c/N queue which accommodates the mobility of producers in addition to the in-network caching and consumer driven transport of ICN.
- We use this model to characterize the distribution of content delivery time (of the network) which is an important design parameter for our mechanism (and also in general).

The rest of the paper is organized as follows. In Section II we discuss the existing literature related to our work. Then, Section III describes the proposed strategy for addressing producer mobility. We discuss our analytical model in Sections IV and V. The performed simulations and results are presented in Section VI. Finally, Section VII concludes the paper.

This research was supported in part by Singapore Ministry of Education Academic Research Fund Tier 1 (R-263-000-D62-114).

II. RELATED WORK

The authors in [2] use the PIT entries of an interest packet to track the current location of a producer. This methodology exploits the fact that a data packet traverses the reverse path of the interest packet. There are proposals to use tunneling based approaches [3], [4] and rendezvous servers [5]. Mechanisms to address micro mobility of producers have been discussed in [6], [7]. Authors in [8] use geo-location to make forwarding decisions by adding new rules to FIB while authors in [9] propose to use additional data structures like recent satisfied list and neighbor satisfied list for choosing the ideal neighbor for forwarding. However, no analytical model is presented in [2]–[4], [6]–[8] to evaluate the performance or gain insights in to the impact of producer mobility and system parameters on ICN performance.

Modeling the transport performance and the mobility of nodes for the current Internet is a well explored problem in the literature. Authors of [10] propose an analytical model of content centric network’s in-network caching and consumer driven transport. A closed form expression is derived for the mean throughput of the network as a function of the cache miss probability at the intermediate nodes, content’s popularity, and the size of the caches. Using the proposed models, the authors characterize the throughput and the content delivery time. In [11], the authors develop an analytical model of bandwidth and cache sharing with limited resources. Under the assumptions that the consumers utilize the bandwidth fairly and the in-network cache replacement policy is least recently used (LRU), the authors characterize the average content delivery time as a closed form expression. This characterization is used to trade-off between the limited network resources and the performance of the network. Recently, the authors in [12] have developed an analytical model for content transfer in ICN. In addition to the in-network caching and consumer driven transport, the authors have considered the queuing delay at the routers in their analytical model. While the mentioned literature model and analyze different components of ICN, to the best of our knowledge, there is no work which models the consumer application while taking into account the in-network caching at routers and the mobility of producers.

III. HOP-COUNT BASED FORWARDING

In this section, we discuss our proposed hop-count based forwarding strategy for producer mobility.

A. Interest Format

To the interest format specified in [1], we propose to add two fields, viz., hop-count threshold (θ) and hop-count (α). Initially, the consumer sets the value of α to 0 and is incremented at every subsequent router. Depending on the previously received data, the consumer decides the value of θ . When the router

receives an interest, it makes the forwarding decision using the values of α and θ as described in Section III-B. The router drops the interest when α exceeds the Time To Live (TTL) value (the definition of TTL is similar to that in the Internet Protocol). The data packet too has the hop-count field as the consumer requires it to estimate θ .

B. Forwarding Strategy

1) *At the consumer:* The consumer sends an interest to request any data with its corresponding name. The hop-count value is set to zero at the consumer and then incremented at every subsequent router. The first interest is broadcasted since the producer's whereabouts is not known. Therefore, θ is set to zero ($\alpha := 0$). Let us assume that the value of the hop-count field in the data corresponding to the first interest is α_d . Then for the subsequent interests, θ is set to $\alpha_d - 1$ ($\theta := \alpha_d - 1$). Whenever a subsequent data arrives, the value of θ is updated. As θ is set to $\alpha_d - 1$, the interest is broadcasted by the router connected to the producer's access point. In the event of a retransmission time out, the hop-count threshold is decremented by one ($\theta := \theta - 1$) and then the interest is retransmitted. When the producer is unreachable, the value of θ is reduced thereby increasing the number of nodes where the interest is forwarded. On a successful receipt of data θ is reset to $\alpha_d - 1$. The Algorithm 1 summarizes the updation of θ at the consumer. We intuitively note that θ depends on the network topology and the producer's movement.

Algorithm 1: Updating the value of θ

```

 $\alpha := 0$ 
if First interest then
  |  $\theta = 0$ 
else if Received DatP then
  |  $\theta := \alpha_d - 1$ 
else if Retransmission time out then
  |  $\theta := \max\{\theta - 1, 0\}$ 

```

2) *At the router:* On an interest arrival, the router looks up its CS for the requested data. If a hit occurs, the router serves the data from its CS. Otherwise, the PIT of the router is looked up for any pending interest for the same data. If any interest is already pending, the corresponding PIT entry is updated to accommodate the current interest as well. When a miss occurs both at the CS and the PIT, the router forwards the interest. This is the default ICN behavior [1]. In our proposed strategy, when the router is required to forward the interest, it compares α and θ . When $\alpha < \theta$, the FIB is looked up and the interest is forwarded to the best matched face. On the other hand, if $\theta \leq \alpha < \text{TTL}$, the interest is broadcasted to all its neighbors and the router drops the interest if $\alpha \geq \text{TTL}$. Algorithm 2 summarizes the interest forwarding strategy at the router.

When a data arrives at the router, it looks for the corresponding interest in the PIT. If an entry exists, the data is cached in the CS and the data is forwarded to the corresponding faces. In ICN, the data always traverses the reverse path of the interest. Therefore, we can infer that the producer is reachable from the face on which the data has arrived. This information is updated in the router's FIB. Algorithm 3 summarizes the data forwarding strategy at the router.

IV. CONSUMER BEHAVIOR

In this section, we develop a model to characterize the content delivery time (also referred to as the sojourn time) as experienced by the consumer. We consider the content

Algorithm 2: Interest forwarding

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if (Match found in CS) then
  | Reply with data
else if Match found in PIT then
  | Update the PIT entry
else if  $\alpha < \theta$  then
  | Forward interest to face matched using FIB
else if  $\theta \leq \alpha < \text{TTL}$  then
  | Broadcast interest to all the neighbors
else
  | Drop interest

```

Algorithm 3: Data forwarding

```

if (Match found in PIT) then
  | Forward data to corresponding faces
  if FIB entry for the data  $\neq$  data incoming-face then
    | Update the FIB entry
else
  | Drop unsolicited data

```

universe is partitioned into K equisized popularity classes. Consumers generate requests with a mean arrival rate of λ . The request for a content from class κ is generated with a rate of $\lambda_\kappa = p_\kappa \lambda$ where p_κ follows a Zipf's distribution with parameter α . Contents are divided into data chunks. While the contents can comprise of variable number of data chunks, the size of the data chunk is fixed and denoted by D . Let σ be the average size of the content (in terms of number of data chunks).

Let c be the maximum number of unserved interests a consumer has already requested and $(N - c)$ be the maximum number of interests waiting to be requested at the consumer (N is the maximum number of unserved interests). Let us consider a generic consumer generating interests for a given content. For simplicity, we consider an arbitrary content class (and hence drop the class index κ from the discussion in this section). We assume the time required for a requested interested to be served (also referred to as the service time) follows an exponential distribution with mean μ . Estimation of μ is discussed in Section V. Using the assumptions above, we model the consumer using a GI/M/c/N queue.

We assume that 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) $a^*(s)$, and mean $1/\lambda$. Let successive interest arrivals occur at time epochs t_0, t_1, t_2, \dots and the time epoch just before the arrival instant t_n be t_n^- (hereafter referred to as pre-arrival epoch). We consider t_n^- , $n > 0$ to be the embedded points. We define the state of the system at time t_i^- as $\{N_s(t_i^-)\}$, where $N_s(t_i^-)$ is the number of unserved interests in the system. We note that the process $\{N_s(t_i^-)\}$ is an embedded Markov chain. We use π_n to denote the probability that there are n interests in the system at the pre-arrival epoch.

Now, we look at the system size at the pre-arrival epoch. Let d_k ($k \geq 0$) be the probability that k interests are served during an inter-arrival time given that the number of unserved interests is c during the inter-arrival time duration. Let $a_{k+1,j}$ be the probability that an arriving interest finds the system in state k , ($k \leq c - 1$) while the next arriving interest finds the system in state j , ($0 \leq j \leq k$). This implies that $k + 1 - j$ interests have been served during the inter-arrival time of a interest. Similarly, let $b_{k+1,j}$ be the probability that an arriving interest finds the system in state k , ($k \geq c$) and the next arriving interest finds

the system in state j , ($0 \leq j \leq c-1$). Then,

$$d_k = \int_0^\infty \frac{(c\mu t)^k}{k!} e^{-c\mu t} dA(t), \quad (1)$$

$$a_{k,j} = P(N_s(t_i^-) = j | N_s(t_{i-1}^-) = k-1) \\ \text{where } (1 \leq k \leq c), (0 \leq j \leq k) \\ = \binom{k}{j} \sum_{l=0}^{k-j} (-1)^{k-j+l} \binom{k-j}{l} a^*(\mu(k-l)), \quad (2)$$

$$b_{k,j} = P(N_s(t_i^-) = j | N_s(t_{i-1}^-) = k-1) \\ \text{where } (k-1 \geq c), (0 \leq j \leq c-1), \\ = \int_0^\infty \int_0^t \frac{(\mu c)^{k-c} u^{k-c-1} e^{-c\mu u}}{(k-c-1)!} \binom{c}{j} e^{-\mu j(t-u)} \\ (1 - e^{-\mu(t-u)})^{c-j} dudA(t) \\ = \frac{(\mu c)^{k-c}}{(k-c-1)!} \binom{c}{j} \int_0^\infty \int_0^t g(u)h(t-u)dudA(t), \quad (3)$$

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 [13]. 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

$$\int_0^\infty e^{-st} h(t) dt = \int_0^\infty e^{-st} e^{-\mu j t} (1 - e^{-\mu t})^{c-j} dt \\ = \frac{\Gamma(j+s/\mu)\Gamma(c-j+1)}{\mu\Gamma(c+s/\mu+1)}.$$

In this paper, we consider the buffer to be of finite size (a GI/M/c/N queue). Hence, the state space of our system is given by $\Theta = \{(k), 0 \leq k \leq N\}$. Observing the state of the system at two consecutive embedded points, we have the one step transition probability matrix (TPM) \mathbf{E} as given by Equation (4). Using the TPM, we can solve for the stationary probability vector π .

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

Next we evaluate the sojourn time of an interest. 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 sent immediately (no waiting time). Second, there are c pending interests and hence the arriving request is buffered. Let $S(t)$ be the CDF of the sojourn time. Then

$$S(t) = \sum_{k=0}^{c-1} \pi_k F(t) + \sum_{k=c}^N \pi_k (G_k * F)(t). \quad (5)$$

Here π_k is the probability of the system being in state k , $F(t)$ and $G_k(t)$ are the CDFs of the service and the waiting time when the state of the system is k . As we assume the system

to be a GI/M/c/N queue, $F(t)$ and $G(t)$ follow the exponential and the Erlang distributions respectively, and are given by

$$F(t) = 1 - \mu e^{-\mu t} \quad (6)$$

$$G_k(t) = 1 - \sum_{j=0}^{k-c} \frac{(c\mu t)^j e^{-c\mu t}}{j!}. \quad (7)$$

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

$$H_k(t) = \int_0^t \left(1 - \sum_{j=0}^{k-c} \frac{(c\mu y)^j e^{-c\mu y}}{j!} \right) \mu e^{-\mu(t-y)} dy \\ = \int_0^t \mu e^{-\mu(t-y)} dy \\ - \sum_{j=0}^{k-c} \frac{(c\mu)^j \mu e^{-\mu t}}{j!} \int_0^t y^j e^{-(c-1)\mu y} dy \\ = (1 - e^{-\mu t}) - \sum_{j=0}^{k-c} \frac{(c\mu)^j \mu e^{-\mu t}}{((c-1)\mu)^{j+1}} \\ \int_0^t \frac{((c-1)\mu)((c-1)\mu y)^j e^{-(c-1)\mu y}}{j!} dy \\ = (1 - e^{-\mu t}) - \sum_{j=0}^{k-c} \frac{(c\mu)^j \mu e^{-\mu t}}{((c-1)\mu)^{j+1}} \\ \left(1 - \sum_{i=0}^j \frac{((c-1)\mu)^i}{i!} e^{-(c-1)\mu t} \right). \quad (8)$$

Using Equations (5), (6) and (8), we get

$$S(t) = \sum_{k=0}^{c-1} \pi_k (1 - \mu e^{-\mu t}) + \\ \sum_{k=c}^N \pi_k \left[(1 - e^{-\mu t}) - \sum_{j=0}^{k-c} \frac{(c\mu)^j \mu e^{-\mu t}}{((c-1)\mu)^{j+1}} \right. \\ \left. \left(1 - \sum_{i=0}^j \frac{((c-1)\mu)^i}{i!} e^{-(c-1)\mu t} \right) \right]. \quad (9)$$

V. ESTIMATION OF μ

In this section, we discuss our analytical model for characterizing the average service time ($1/\mu$) for a mobile producer and derive a closed form expression for the same.

A. In-network caching

First we model the ICN in-network caching and in order to do so, we need to estimate the cache miss probabilities at the intermediate nodes along the path of requests. Let $m_\kappa(i)$ be the cache miss probability of a content of class κ at the intermediate node i . Under the assumption that all caches implement the LRU cache replacement policy, $m_\kappa(i)$ is evaluated by the following expression [10]:

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

Again, for simplicity, we consider an arbitrary content class and omit the class index κ . The round trip time (RTT) between the consumer and node i is denoted by $t(i)$. We can estimate $t(i)$ as follows:

$$t(i) = \sum_{j=1}^{i-1} \left(\frac{D}{B_j^{j+1}} + 2R_j^{j+1} \right). \quad (10)$$

Here D is the size of the data chunk, B_j^i is the bandwidth of the link between nodes i and j , and R_j^i is the propagation delay between nodes i and j . We now consider the impact of producer's movement using the following two scenarios.

B. Before hand-off

The average service time in this case is evaluated as 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:

$$f(i) = (1 - m(i)) \prod_{j=1}^{j=i-1} m(j). \quad (11)$$

The average service time, $T_1(n)$, for this case can be calculated as:

$$T_1(n) = \sum_{i=1}^n f(i)t(i). \quad (12)$$

Here, the producer is the n^{th} node. 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 [14]. We denote the expectation of this time by u_1 . Then, u_1 is evaluated as follows.

$$u_1 = \frac{\pi R}{2v}. \quad (13)$$

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 [14] for more details.

C. 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 Forwarding Information Bases (FIBs) need to be updated. 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

$$T_2 = T_1(n) + u_2 + T_1(\hat{n}), \quad (14)$$

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:

$$q = \frac{u_1}{u_1 + u_2}. \quad (15)$$

Using Equations (12) and (14), we can estimate the mean service time, $\frac{1}{\mu}$, of our system as follows:

$$\begin{aligned} \frac{1}{\mu} &= qT_1(n) + (1 - q)T_2 \\ &= T_1(n) + (1 - q)(u_2 + T_1(\hat{n})). \end{aligned} \quad (16)$$

The value of u_2 depends on the approach used for updation. For example, u_2 for the approach in [15] can be considered to be a constant. For the mechanism proposed in our paper, we evaluate u_2 as follows.

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

$$H(z) = E[z^R] = E[z^{\sum_{i=1}^S T_i}]. \quad (17)$$

By conditioning Equation (17) on the value of n we get

$$\begin{aligned} H(z) &= E \left[\sum_{n=1}^{\infty} z^{\sum_{i=1}^n T_i} P(S = n) \right] \\ &= \frac{pG_T(z)}{1 - (1 - p)G_T(z)}. \end{aligned} \quad (18)$$

Using Equation (18), we evaluate the mean updation time u_2 follows

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

VI. SIMULATION RESULTS

In this section, we compare and analyze the numerical results of our analytical model with simulation results. We use the NS-3 based ndnSIM [16] to perform our simulations.

We consider real life mobility traces to model the producer mobility. In [17], 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) is captured every 7 seconds. We use the GPS co-ordinates and the timestamps from this trace to model the movement of the producer. The consumer is assumed to be stationary. 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.

We assume the inter arrival time between two consecutive interests in our system (described in Section IV) to follow an

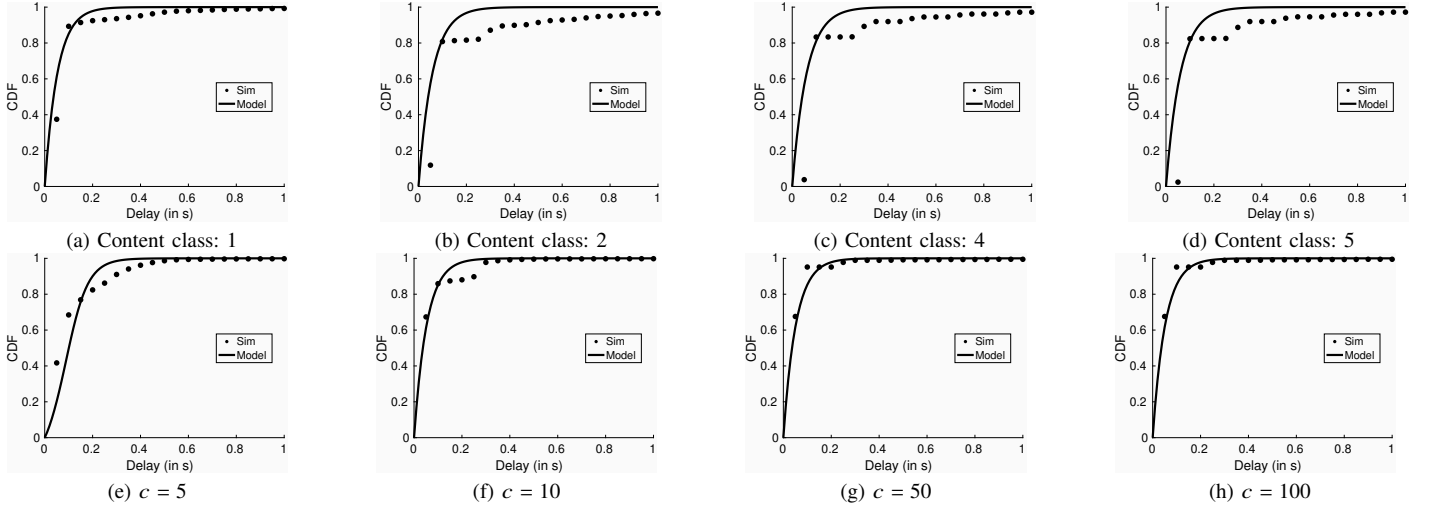


Fig. 1. The CDF of content delivery time obtained from the simulations and the analytical model is compared here. (a)-(e): CDFs for different content classes are shown. (f)-(i): CDFs for consumers with different c are shown. (j)-(l) CDFs for different cache sizes are shown.

exponential distribution with a mean rate λ . Then $b_{k,j}$ is given by:

$$b_{k,j} = \lambda \frac{(\mu c)^{k-c} c!}{j! \mu (\lambda + c \mu)^{k-c}} \frac{\Gamma(j + \lambda/\mu)}{\mu \Gamma(c + \lambda/\mu + 1)}. \quad (19)$$

A. Multiple Content classes

In this scenario, we consider the total number of content classes to be 5 and each content class consists of 1000 different contents. The size of every content is one data chunk and the data chunk itself has a size of 1 KB. The request generation of each content is Poisson. The most popular class has an average arrival rate of 100 interests per second and the arrival rates of other classes is scaled accordingly. The value of c is set to 10 and the cache size is 500 data packets. The obtained results are depicted in Figure 1a-1d. We can observe that for content class one 90% of the traffic incur a delay of 0.1 s or less. This can be attributed to the in-network caching. As class one is the most popular class, the probability of the contents being present in the caches is high. As we go further down the classes this delay increases as 0.25 s, 0.3 s, 0.375s and 0.4 s for classes 2, 3, 4, and 5.

B. Consumers with different values of c

In this scenario, we consider consumers with $c \in [5, 10, 50, 100]$ (non-aggressive to aggressive). The arrival rate at all the consumers is 100 requests per second. The cache size is set to 500 data packets. Figure 1e-1h plot the obtained results. We observe that when $c = 5$ the CDF reaches the value 1 for the incurred delays of 0.5 s, 0.4 s, 0.1 s and 0.1 s for the c values of 5, 10, 50 and 100 implying that the consumer can minimize the maximum incurred delay by increasing the value of c (though it is not a globally optimal solution).

VII. CONCLUSION

Vehicular systems are increasingly becoming an integral part of today's Internet and thus of importance for the future Internet architectures. In this paper, we proposed a mechanism to support producer mobility in ICN. Further, we developed an analytical model which captures the interactions of the mobile producer in ICN with the consumer application as well as the

in-network caching. We modeled the behavior of the consumer application using a GI/M/c/N queue and then derived a closed form expression for average content delivery time to evaluate the impact of mobile producer on the consumer. We evaluated the performance of our mechanism and validated the accuracy of our model using simulations and numerical results.

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