Performance Modeling for Application-Level Integration of Heterogeneous Wireless Networks

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Abstract—The integration of different wireless networks to provide seamless and continuous network access services is a major issue in beyond-third-generation (B3G) networks. To avoid modifying the existing protocols in the network nodes, the application-level approach is proposed for heterogeneous network integration. In the application-level integration, a mobility gateway (MG) is introduced to serve as an agent through which users can use different kinds of mobile devices through different kinds of networks to access Internet applications. There are two major tasks in an MG, including content format translation and data tunneling for handoff users. When the service area of an MG is larger, the MG must handle the content format translation for more users, and the computation overhead of an MG increases significantly. On the other hand, when the service area of an MG shrinks, a served user more likely hands off between different MGs, and more network resources are consumed to tunnel the data for handoff users. In this paper, an analytical model is proposed, and simulation experiments are conducted to study how to properly plan the service area of an MG so that better system performance can be achieved.

Index Terms—Analytical model, application-level integration, content format translation, mobility gateway (MG), tunneling.

I. INTRODUCTION

I N RECENT YEARS, technologies for wireless networks, such as terrestrial cellular systems (e.g., Universal Mobile Telecommunications System) [1], wireless local area networks (WLANs) [2], and wireless personal area networks (WPANs) [3], [4], have evolved quickly. This huge evolution, together with the advances in the computing capability of mobile devices, has led to the use of different kinds of mobile devices to

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Fig. 1. General network architecture.

access Internet services. The integration of different networks (also known as heterogeneous networks) to provide seamless and continuous network access services is one of the major issues in beyond-third-generation or fourth-generation networks. Several studies [5]–[9] have been conducted for the integration of heterogeneous networks. Due to the diversity of different network protocols, most of the previous studies modify the existing protocols in the network nodes for interworking between heterogeneous networks, which may significantly increase the deployment cost. Therefore, the "application-level" approach [10], [11] is proposed for the heterogeneous network integration without modification.

Fig. 1 illustrates the general network architecture for the application-level integration of heterogeneous networks. The mobility gateway [MG; see Fig. 1(1)] is the primary serving node through which users can use different kinds of mobile devices [see Fig. 1(3)] through different kinds of networks to access Internet applications [see Fig. 1(2)]. The MG maintains the session mobility, the personal mobility, and the terminal mobility for the serving users, whose details can be found in [12]. With the exception of the three kinds of mobility, a content format translation function is accommodated in the MG to encapsulate the content that is obtained from application servers with the format that can be displayed on mobile devices. To distribute the load of the MGs, the network architecture follows a distributed gateway approach, where each MG serves one or more WLANs, WPANs, or cellular networks.

Before the user gains the service of the MG, he/she logs in into the MG. Then, the user can activate the Internet application through the MG that serves as an agent for the user and adjusts the content format of the application data to be appropriately



Fig. 2. MG service area layout.

displayed on the mobile devices. During the execution of an application, the mobile user may move out of the service area of an MG and move into the service area of another. At this moment, a tunnel is created between the new and old MGs. Then, the old MG will forward the application data to the new MG, and the mobile user can continue the application in the new MG.

As described above, the major tasks of an MG include content format translation for different types of mobile devices and user data tunneling for handoff users. When the service area of an MG is larger, the MG must handle the content format translation for more users within its service area, and the computation overhead increases significantly. On the other hand, when the service area of an MG shrinks, a served user more likely handoffs between different MGs, and more network resources are required to tunnel the data. Thus, the setup of an MG's service area may significantly affect the performance of the heterogeneous network integration. There is no previous work that addresses this issue. In this paper, we propose an analytical model and conduct simulation experiments to study how to adjust the service area of an MG. Our analytical model is general enough to provide complete performance analysis for the setup of the service area of an MG.

The rest of this paper is organized as follows. Section II proposes the analytical model. In Section III, we study the impacts of several factors on the network performance based on our analytical model. Section IV gives a concluding remark.

II. ANALYTICAL MODEL

This section proposes the analytical model. We consider the "application layer" performance for the MG, which has never been treated in any previous work. Instead of studying the dropping or blocking probabilities for the sessions, we focus on the analysis for the scalability issue on the MG that integrates the heterogeneous wireless networks. In other words, we study how to scale the capacity of the MG. Based on the random-walk model in [13], our model considers an *n*-layer hierarchical hexagonal network configuration to fit one of the characteristics

of the heterogeneous wireless networks, i.e., different sizes of the coverage areas of WPANs, WLANs, and cellular networks. Based on this network configuration, we derive a general analytical model to study the effects of different kinds of user behaviors (or data traffic patterns) on the application layer performance of an MG. The random walk model in [13] has been widely applied in many personal communication service studies [14]-[20] to solve different problem domains. Most of these studies target on analyzing the performance of the radio resource allocation and mobility management algorithms, and consider at most three-layer hierarchical networks, which is not sufficient to provide performance analysis for an MG where an *n*-layer hierarchical network structure is required. In this paper, we focus on proposing a new modeling technique for the *n*-layer hierarchical hexagonal networks, which can be considered as one of our major contributions.

Define a coverage area (CA) as the service range of a wireless network. One or more CAs can be served by an MG. In other words, a service area of an MG consists of one or more CAs. As shown in Fig. 2, each CA is assumed to be independent and identically distributed (i.i.d.) and is shaped to a hexagon. An n-layer MG service area is partitioned into seven (n-1)-layer MG service areas (also known as the sublayer service areas) and consists of 7^{n-1} CAs. Let type $\langle x, n-1 \rangle$ denote one (n-1)-layer MG service area in an *n*-layer MG service area, where $\langle 0, n-1 \rangle$ represents the central (n-1)-layer MG service area, and (1, n-1) represents one of the six surrounding (n-1)-layer MG service areas. The sublayer service areas of the same type are indistinguishable in terms of movement pattern because they are at the symmetrical position. For example, a three-layer MG service area contains seven two-layer MG service areas and consists of 49 CAs. The central sublayer service area is type (0, 2). The six surrounding sublayer service areas have the same type $\langle 1, 2 \rangle$.

Based on the above labeling for the MG service area, we use the random walk model to model the user movement, where the user moves to each of the neighboring MG service areas with an equal probability of one sixth. Consider a heterogeneous network that consists of an *n*-layer MG service area. Let (x, n - 1) be the state of the random walk model. For x = 0 or 1, the state (x, n - 1) is transient; that is, the user is in one of the sublayer MG service areas of type $\langle x, n - 1 \rangle$. The state (2, n - 1) is absorbing; that is, the user crosses the boundary of the *n*-layer MG service area from the sublayer MG service area with the type $\langle 1, n - 1 \rangle$. Let $p_{(x,n-1),(x',n-1)}$ be the one-step transition probability from state (x, n - 1) to state (x', n - 1), i.e., the probability that the user moves from an $\langle x, n - 1 \rangle$ sublayer MG service area to an $\langle x', n - 1 \rangle$ sublayer MG service area to an each of this random walk model for an *n*-layer MG service area can be expressed as

$$\mathbf{P} = \begin{pmatrix} 0 & 1 & 0\\ 1/6 & 1/3 & 1/2\\ 0 & 0 & 1 \end{pmatrix}.$$
 (1)

We use the Chapman–Kolmogorov equation [21] to compute the probability that a user moves from an *n*-layer MG service area to another for a certain number of movements. For $k \ge 1$, we have

$$\mathbf{P}^{(k)} = \begin{cases} \mathbf{P}, & \text{if } k = 1\\ \mathbf{P} \times \mathbf{P}^{(k-1)}, & \text{if } k > 1. \end{cases}$$
(2)

An element $p_{(x,n-1),(x',n-1)}^{(k)}$ in $\mathbf{P}^{(k)}$ is the probability that the random walk moves from state (x, n-1) to state (x', n-1) with exact k steps. Define $p_{k,(x,n-1),(2,n-1)}$ as the probability that a user initially resides at an $\langle x, n-1 \rangle$ sublayer MG service area, moves into a $\langle 1, n-1 \rangle$ sublayer MG service area at the k-1st step, and then moves out of the n-layer MG service area at the kth step. Then, $p_{k,(x,n-1),(2,n-1)}$ can be expressed as

$$\begin{split} p_{k,(x,n-1),(2,n-1)} & \text{for } k = 1 \\ & = \begin{cases} p_{(x,n-1),(2,n-1)}, & \text{for } k = 1 \\ p_{(x,n-1),(2,n-1)}^{(k)} - p_{(x,n-1),(2,n-1)}^{(k-1)}, & \text{for } k > 1 \end{cases} \end{split}$$

which can be solved by using transition probability matrices (1) and (2).

Let $t_{a,i}$ be the residence time for a user at CA *i*. Since each CA is i.i.d., $t_{a,i}$'s are i.i.d. random variables. Suppose that $t_{a,i}$ has the general density function $f_a(\cdot)$. For a homogeneous network, for $i \neq j$, we have

$$f_a(t_{a,i}) = f_a(t_{a,j}) = f_a(t_a)$$

Let t_{A_n} be the time period when a user resides in an *n*-layer MG service area, $f_{A_n}(\cdot)$ be the density function of t_{A_n} , and $f_{A_n}^*(s)$ be the Laplace transform of $f_{A_n}(\cdot)$. Suppose that during $t_{A_n}^{(k)}$, the user visits k sublayer MG service areas of an *n*-layer MG service area [i.e., k (n-1)-layer MG service areas]. We have $t_{A_n}^{(k)} = t_{A_{n-1},1} + t_{A_{n-1},2} + \cdots + t_{A_{n-1},k}$, where $t_{A_{n-1},i}$ denotes the user residence time at the *i*th sublayer MG service area

vice area. Density function $f_{A_n}^{(k)}(\cdot)$ for $t_{A_n}^{(k)}$ can be derived as follows:

$$f_{A_n}^{(k)}\!\left(t_{A_n}^{(k)}\right) = \int_{t_{A_{n-1},1=0}}^{t_{A_n}^{(k)}} \int_{t_{A_{n-1},2=0}}^{t_{A_{n-1},1}} \cdots \int_{t_{A_{n-1},k-1}}^{t_{A_n}^{(k)}-t_{A_{n-1},1}\cdots t_{A_{n-1},k-2}} \\ \times \left(\prod_{i=1}^{k-1} f_{A_{n-1}}(t_{A_{n-1},i})\right) f_{A_{n-1}} \\ \times \left(t_{A_n}^{(k)}-t_{A_{n-1},1}-t_{A_{n-1},2},\dots,-t_{A_{n-1},k-1}\right) \\ \times dt_{A_{n-1},k-1},\dots, dt_{A_{n-1},2}dt_{A_{n-1},1}.$$
(3)

Let $q_{(x,n-1)}$ be the probability that a user enters the *n*-layer MG service area through an $\langle x, n-1 \rangle$ sublayer MG service area, the user must cross the $\langle 1, n-1 \rangle$ sublayer service area. Thus, we have $q_{(1,n-1)} = 100\%$. Let $q_{(1,n-1)}p_{k,(1,n-1),(2,n-1)}$ be the probability that a user enters an *n*-layer MG service area through a $\langle 1, n-1 \rangle$ sublayer MG service area at the first step, moves into a $\langle 1, n-1 \rangle$ sublayer MG service area at the *k*-1st step, and then moves out of the *n*-layer MG service area at the *k*th step. Thus, by using (3), density function $f_{A_n}(\cdot)$ for the user residence time in an *n*-layer MG service area is expressed as

$$f_{A_n}(t_{A_n}) = \sum_{k=1}^{\infty} q_{(1,n-1)} p_{k,(1,n-1),(2,n-1)} f_{A_n}^{(k)} \left(t_{A_n}^{(k)} \right).$$
(4)

Denote $f_{A_{n-1}}^*(s)$ as the Laplace transform of $f_{A_{n-1}}(\cdot)$. Then, from (3) and the Laplace transform convolution rule [21], we have the Laplace transform $f_{A_n}^{(k)*}(s)$ for $f_{A_n}^{(k)}(\cdot)$ as

$$f_{A_n}^{(k)*}(s) = \left[f_{A_{n-1}^*}(s)\right]^k, \text{ for } n > 1.$$
(5)

Do the Laplace transform on both sides of (4) and then apply it to (5). For n > 1, we have the Laplace transform $f_{A_n}^*(s)$ for $f_{A_n}(\cdot)$ as

$$f_{A_n}^*(s) = \sum_{k=1}^{\infty} q_{(1,n-1)} p_{k,(1,n-1),(2,n-1)} f_{A_n}^{(k)*}(s)$$
$$= \sum_{k=1}^{\infty} q_{(1,n-1)} p_{k,(1,n-1),(2,n-1)} \left[f_{A_{n-1}^*}(s) \right]^k.$$
(6)

Consider the case where n = 1. The user residence time in a one-layer MG service area is equal to that in a CA. Thus, we have

$$f_{A_1}^*(s) = f_a^*(s). (7)$$

From (6) and (7), we have the following recursive function to obtain the Laplace transform $f_{A_n}^*(s)$ for $f_{A_n}(\cdot)$.

$$f_{A_n}^*(s) = \begin{cases} f_a^*(s), & \text{for } n = 1\\ \sum_{k=1}^{\infty} q_{(1,n-1)} p_{k,(1,n-1),(2,n-1)} \left[f_{A_{n-1}^*}(s) \right]^k, & \text{for } n > 1. \end{cases}$$
(8)



Fig. 3. Timing diagram for the session of a user.

The mean of the residence time in an *n*-layer MG service area (i.e., t_{A_n}) can be derived by using

$$E[t_{A_n}] = (-1) \frac{df_{A_n}^*(s)}{ds} \bigg|_{s=0}.$$
(9)

In this paper, we target to measure the average load index and the total load index in the application layer of an MG. We make the following three assumptions.

Assumption 1: The session arrivals in a CA form a Poisson process with rate λ_o .

Assumption 2: The elapsed time (denoted as t_s) of the session is exponentially distributed with density function $f_s(t_s) = \mu_s e^{-\mu_s t_s}$ and mean $1/\mu_s$. We consider the following two situations that enforce the ongoing session to be completed.

- 1) The user stops the application, and the ongoing session is completed.
- 2) The ongoing session is completed due to the fact that the wireless connection is lost (for example, the wireless resource is not enough to serve the session).

Assumption 3: The resource for the application layer of an MG is not limited. That is, there is no blocking and dropping for any arriving session.

Let $t_{do,n}$ and $t_{dh,n}$ be the dwell (MG processing) time of an original session and a handoff session within an n-layer MG service area, respectively. Fig. 3 shows the timing diagram for the session of a user. Dwell time $t_{do,n}$ for an original session is the period between the time when the new session is initiated at the *n*-layer MG service area $A_{n,0}$ and the time when the session is completed at the service area $A_{n,0}$ or when the user moves to another service area. Let $t_{A_{n,i}}$ be the residence time of the user in an *n*-layer MG service area $A_{n,i}$, and let τ_{A_n} be the interval between the time when the session arrives and the time when the user moves out of the *n*-layer MG service area $A_{n,0}$. Therefore, $t_{do,n} = \tau_{A_n}$ if the user moves to another service area during the session, or $t_{do,n} = t_s$ if the session is completed at the service area. Fig. 3 shows the case where $t_{do,n} = \tau_{A_n}$. It is obvious that $t_{do,n} \neq t_{A_{n,i}}$. Then, from [22] and [23], $t_{do,n}$ can be expressed as

$$t_{do,n} = \min(t_s, \tau_{A_n}). \tag{10}$$

Suppose that τ_{A_n} has the distribution function $R(\tau_{A_n})$, the density function $r(\tau_{A_n})$, and the Laplace transform $r^*(s)$. From the renewal theory [24], τ_{A_n} is the residual life of the residence time of the user in an *n*-layer MG service area, and we have

$$r(\tau_{A_n}) = \frac{1}{E[t_{A_n}]} \int_{t_{A_n}=\tau_{A_n}}^{\infty} f_{A_n}(t_{A_n}) dt_{A_n}$$
(11)

$$r^*(s) = \frac{1}{sE[t_{A_n}]} \left[1 - f^*_{A_n}(s) \right].$$
(12)

From (10)–(12), expected dwell time $E[t_{do,n}]$ of an original session can be derived as follows:

$$E[t_{do,n}] = E\left[\min(t_{s}, \tau_{A_{n}})\right]$$

$$= \int_{t_{s}=0}^{\infty} \int_{\tau_{A_{n}}=0}^{t_{s}} \tau_{A_{n}}r(\tau_{A_{n}})f_{s}(t_{s})d\tau_{A_{n}}dt_{s}$$

$$+ \int_{t_{s}=0}^{\infty} \int_{\tau_{A_{n}}=t_{s}}^{\infty} t_{s}r(\tau_{A_{n}})f_{s}(t_{s})d\tau_{A_{n}}dt_{s}$$

$$= \mu_{s}\left\{\left(-1\right)\frac{d}{ds}\left[\frac{r^{*}(s)}{s}\right]\Big|_{s=\mu_{s}} - \frac{r^{*}(s)}{s^{2}}\Big|_{s=\mu_{s}}\right\}$$

$$+ \left\{\frac{1}{\mu_{s}} - \mu_{s}\left\{\left(-1\right)\frac{d}{ds}\left[\frac{r^{*}(s)}{s}\right]\Big|_{s=\mu_{s}}\right\}\right\}$$

$$= \frac{1}{\mu_{s}} - \frac{1 - f_{A_{n}}^{*}(\mu_{s})}{\mu_{s}^{2}E[t_{A_{n}}]}.$$
(13)

Applying (9), (13) is rewritten as

$$E[t_{do,n}] = \frac{1}{\mu_s} + \frac{1 - f_{A_n}^*(\mu_s)}{\mu_s^2 \left(\frac{df_{A_n}^*(s)}{ds}\Big|_{s=0}\right)}.$$
 (14)

Dwell time $t_{dh,n}$ for a handoff session within an *n*-layer MG service area is the period between the time when the user that is having an ongoing session moves into an MG service area and the time when the user that is having an ongoing session leaves the service area or when the ongoing session is completed at the service area. Suppose that a session hands over *i* times. Let $t_{s,i}$ be the period between the time when the user moves into *n*-layer MG service area $A_{n,i}$ and the time when the session is completed. Period $t_{s,i}$ is called the excess life of t_s . Then, we have $t_{dh,n} = t_{s,i}$ if the ongoing session is completed at the service area or $t_{dh,n} = t_{A_{n,i}}$ if the user having the ongoing session moves to another service area. Fig. 3 shows the case where $t_{dh,n} = t_{s,i}$. Therefore, $t_{dh,n} = t_{A_{n,i}}$ does not always hold. From [22] and [23], $t_{dh,n}$ can be expressed as

$$t_{dh,n} = \min(t_{s,i}, t_{A_{n,i}}).$$

Due to the memoryless property, the excess life of a session has the same (exponential) distribution as the original session time. In other words, for $i \ge 1$

$$f_{s,i}(t_{s,i}) = f_s(t_s) = \mu_s e^{-\mu_s t_{s,i}}.$$
(15)

Then, following the similar derivation for $E[t_{do,n}]$, we have

$$E[t_{dh,n}] = E\left[\min(t_{s,i}, t_{A_{n,i}})\right]$$

$$= \int_{t_{s,i}=0}^{\infty} \int_{t_{A_{n,i}}=0}^{t_{s,i}} t_{A_{n,i}} f_{A_{n}}(t_{A_{n,i}}) \mu_{s} e^{-\mu_{s} t_{s,i}} dt_{A_{n,i}} dt_{s,i}$$

$$+ \int_{t_{s,i}=0}^{\infty} \int_{t_{A_{n,i}}=t_{s,i}}^{\infty} t_{s,i} f_{A_{n}}(t_{A_{n,i}}) \mu_{s} e^{-\mu_{s} t_{s,i}} dt_{A_{n,i}} dt_{s,i}$$

$$= \frac{1 - f_{A_{n}}^{*}(\mu_{s})}{\mu_{s}}.$$
(16)

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If the Laplace transform $f_a^*(s)$ for $f_a(\cdot)$ exists, then we can derive the Laplace transform $f_{A_n}^*(s)$ for $f_{A_n}(\cdot)$ by recursively using (8). In other words, our model can be applied to any CA residence time distribution whose Laplace transform exists.

We use load index $L_{t,n}$ to measure the total load of an MG with the *n*-layer MG service area, which is defined as

$$L_{t,n} = E[N_{o,n}]E[t_{do,n}] + \beta E[N_{h,n}]E[t_{dh,n}]$$
(17)

where $E[N_{o,n}]$ and $E[N_{h,n}]$ are the expected numbers of original and handoff sessions within an *n*-layer MG service area, respectively, and β is the factor that is used to normalize the load of handoff sessions over that of original sessions. Since handoff sessions introduce both content format translation and tunneling overhead, β is intuitively larger than one. Besides $L_{t,n}$, average load index $L_{a,n}$ is used to measure the average load of a user contributing to an MG with the *n*-layer MG service area, which is defined as

$$L_{a,n} = \frac{E[N_{o,n}]E[t_{do,n}] + \beta E[N_{h,n}]E[t_{dh,n}]}{E[N_{o,n}] + E[N_{h,n}]}.$$
 (18)

The intuition behind $L_{a,n}$ is that, with low $L_{a,n}$, an MG may more likely successfully handle the session for the user. Let $\Lambda_{o,n}$ be the original session arrival rate to an *n*-layer MG service area. Since an *n*-layer MG service area consists of 7^{n-1} CAs, and each CA is i.i.d., we have

$$\Lambda_{o,n} = 7^{n-1} \lambda_o. \tag{19}$$

Denote $\Lambda_{h,n}$ as the handoff session arrival rate to an *n*-layer MG service area. Let $\Pr[t_s > \tau_{A_n}]$ ($\Pr[t_{s,i} > t_{A_{n,i}}]$) be the probability that a new (handoff) session at the MG service area is not completed before the mobile user moves out of the MG service area. Since there is no blocking or dropping for any arriving session, $\Lambda_{h,n}$ can be expressed as

$$\begin{split} \Lambda_{h,n} &= \Lambda_{o,n} \Pr[t_s > \tau_{A_n}] + \Lambda_{h,n} \Pr[t_{s,i} > t_{A_{n,i}}] \\ &= \Lambda_{o,n} \int_{t_s=0}^{\infty} \int_{\tau_{A_n}=0}^{t_s} r(\tau_{A_n}) f_s(t_s) d\tau_{A_n} dt_s \\ &+ \Lambda_{h,n} \int_{t_{s,i}=0}^{\infty} \int_{t_{A_{n,i}}=0}^{t_{s,i}} f_{A_n}(t_{A_{n,i}}) \mu_s e^{-\mu_s t_s} dt_{A_{n,i}} dt_{s,i} \\ & \Lambda_{o,n} \left[1 - f_{s,i}^* - (\tau_{A_n}) \right] + \Lambda_{o,n} f_{s,i}^* - (\tau_{A_{n,i}}) \left[1 - f_{s,i}^* - (\tau_{A_{n,i}}) \right] + \Lambda_{o,n} f_{s,i}^* - (\tau_{A_{n,i}}) \left[1 - f_{s,i}^* - (\tau_{A_{n,i}}) \right] + \Lambda_{o,n} f_{s,i}^* - (\tau_{A_{n,i}}) \left[1 - f_{s,i}^* - (\tau_{A_{n,i}}) \right] + \Lambda_{o,n} f_{s,i}^* - (\tau_{A_{n,i}}) \left[1 - f_{s,i}^* - (\tau_{A_{n,i}}) \right] + \Lambda_{o,n} f_{s,i}^* - (\tau_{A_{n,i}}) \left[1 - f_{s,i}^* - (\tau_{A_{n,i}}) \right] + \Lambda_{o,n} f_{s,i}^* - (\tau_{A_{n,i}}) \left[1 - f_{s,i}^* - (\tau_{A_{n,i}}) \right] + \Lambda_{o,n} f_{s,i}^* - (\tau_{A_{n,i}}) \left[1 - f_{s,i}^* - (\tau_{A_{n,i}}) \right] + \Lambda_{o,n} f_{s,i}^* - (\tau_{A_{n,i}}) \left[1 - f_{s,i}^* - (\tau_{A_{n,i}}) \right] + \Lambda_{o,n} f_{s,i}^* - (\tau_{A_{n,i}}) \left[1 - f_{s,i}^* - (\tau_{A_{n,i}}) \right] + \Lambda_{o,n} f_{s,i}^* - (\tau_{A_{n,i}}) \left[1 - f_{s,i}^* - (\tau_{A_{n,i}}) \right] + \Lambda_{o,n} f_{s,i}^* - (\tau_{A_{n,i}}) \left[1 - f_{s,i}^* - f_{s,i} \right]$$

 $= \frac{\Lambda_{o,n}}{\mu_s E[t_{A_n}]} \left[1 - f_{A_n}^*(\mu_s) \right] + \Lambda_{h,n} f_{A_n}^*(\mu_s).$ (20)

From (20), we have

$$\Lambda_{h,n} = \frac{\Lambda_{o,n}}{\mu_s E[t_{A_n}]}.$$
(21)

Then, $E[N_{o,n}]$ and $E[N_{h,n}]$ can be obtained by applying Little's law [24], i.e.,

$$E[N_{o,n}] = \Lambda_{o,n} \times E[t_{do,n}] \tag{22}$$

$$E[N_{h,n}] = \Lambda_{h,n} \times E[t_{dh,n}].$$
⁽²³⁾

Applying (14), (16), (19), and (21)–(23) can be rewritten as follows:

$$E[N_{o,n}] = 7^{n-1}\lambda_o \left[\frac{1}{\mu_s} + \frac{1 - f_{A_n}^*(\mu_s)}{\mu_s^2 \left(\frac{df_{A_n}^*(s)}{ds}\Big|_{s=0}\right)} \right]$$
(24)
$$E[N_{h,n}] = 7^{n-1}\lambda_o \left[\frac{f_{A_n}^*(\mu_s) - 1}{\mu_s^2 \left(\frac{df_{A_n}^*(s)}{ds}\Big|_{s=0}\right)} \right].$$
(25)

Applying (14), (16), (24), and (25) to (17), we obtain $L_{t,n}$ for an *n*-layer MG service area as

$$L_{t,n} = 7^{n-1} \lambda_o \left\{ \left[\frac{1}{\mu_s} + \frac{1 - f_{A_n}^*(\mu_s)}{\mu_s^2 \left(\frac{df_{A_n}^*(s)}{ds} \Big|_{s=0} \right)} \right]^2 - \frac{\beta \left(1 - f_{A_n}^*(\mu_s) \right)^2}{\mu_s^3 \left(\frac{df_{A_n}^*(s)}{ds} \Big|_{s=0} \right)} \right\}.$$
 (26)

Applying (14), (16), (24), and (25) to (18), we obtain $L_{a,n}$ for an *n*-layer heterogeneous network integration support node service area as

$$L_{a,n} = \mu_s \left\{ \left[\frac{1}{\mu_s} + \frac{1 - f_{A_n}^*(\mu_s)}{\mu_s^2 \left(\frac{df_{A_n}^*(s)}{ds} \Big|_{s=0} \right)} \right]^2 - \frac{\beta \left(1 - f_{A_n}^*(\mu_s) \right)^2}{\mu_s^3 \left(\frac{df_{A_n}^*(s)}{ds} \Big|_{s=0} \right)} \right\}.$$
(27)

In this paper, we take the gamma distribution as an example for the distribution of t_a . This distribution has been widely adopted to simulate the user movement in a mobile networking field [10], [18], [19] and can be used to approximate many other distributions [21]. The gamma distribution with shape parameter α , mean $E[t_a] = 1/\eta_a$, and variance $v_a = 1/\alpha \eta_a^2$ has the following Laplace transform $f_a^*(s)$:

$$f_a^*(s) = \left(\frac{\alpha \eta_a}{\alpha \eta_a + s}\right)^{\alpha}.$$
 (28)

The analytical model is validated by simulation experiments of a discrete event-driven simulation model, which has been widely adopted to simulate the mobile communications networks in several studies [19], [25], [26]. The simulation model

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IABLE I
COMPARISON BETWEEN THE ANALYTICAL AND SIMULATION RESULTS
1-layer MG service area ($\lambda_o = 10\mu_s, \eta_a = \frac{2}{3}\mu_s, \beta = 3$)

TADLE

v_a	$\frac{10}{\eta_a^2}$	$\frac{5}{\eta_a^2}$	$\frac{1}{\eta_a^2}$	$\frac{1}{5\eta_a^2}$	$\frac{1}{10\eta_a^2}$
$L_{t,1}$ (Analytical)	8.20469	8.32105	10.8	13.3081	13.8159
$L_{t,1}$ (Simulation)	8.17741	8.29956	10.7345	13.2384	13.7795
Error	0.3325%	0.2583%	0.6065%	0.5237%	0.2635%
$L_{a,1}$ (Analytical)	0.820469	0.832105	1.08	1.33081	1.38159
$L_{a,1}$ (Simulation)	0.819325	0.831327	1.074725	1.3269	1.3797
Error	0.1394%	0.0935%	0.4884%	0.2938%	0.1368%

2-layer MG service area ($\lambda_o = 10\mu_s, \eta_a = \frac{2}{3}\mu_s, \beta = 3$)								
v_a	$\frac{10}{\eta_a^2}$	$\frac{5}{\eta_a^2}$	$\frac{1}{\eta_a^2}$	$\frac{1}{5\eta_a^2}$	$\frac{1}{10\eta_a^2}$			
$L_{t,2}$ (Analytical)	64.7695	67.6315	77.6709	83.483	84.4806			
$L_{t,2}$ (Simulation)	64.4942	67.4178	77.1462	83.1602	84.2524			
Error	0.4250%	0.3159%	0.6755%	0.3867%	0.2669%			
$L_{a,2}$ (Analytical)	0.925279	0.966165	1.10958	1.19261	1.20687			
$\overline{L_{a,2}}$ (Simulation)	0.922984	0.96438	1.10583	1.19055	1.20496			
Error	0.2480%	0.1848%	0.3353%	0.1727%	0.1583%			
3-layer MG service area ($\lambda_o = 10\mu_s, \eta_a = \frac{2}{3}\mu_s, \beta = 3$)								
,	MG servic	e area (λ_o	= $10\mu_s$, η_a	$=\frac{2}{3}\mu_s, \beta$	= 3)			
v_a	$\frac{10}{\eta_a^2}$	e area (λ_o) $\frac{5}{\eta_a^2}$	$= 10\mu_s, \eta_a$ $\frac{1}{\eta_a^2}$	$=\frac{\frac{2}{3}\mu_s,\beta}{\frac{1}{5\eta_a^2}}$	$= 3)$ $\frac{1}{10\eta_a^2}$			
$\frac{v_a}{L_{t,3} \text{ (Analytical)}}$	$\frac{\frac{10}{\eta_a^2}}{486.757}$	e area (λ_o) $\frac{\frac{5}{\eta_a^2}}{500.464}$	$= 10\mu_s, \eta_a \\ \frac{\frac{1}{\eta_a^2}}{527.269}$	$=\frac{\frac{2}{3}\mu_s,\beta}{\frac{1}{5\eta_a^2}}$ 538.345	$= 3) \\ \frac{\frac{1}{10\eta_a^2}}{540.078}$			
$ \frac{v_a}{L_{t,3} \text{ (Analytical)}} L_{t,3} \text{ (Simulation)} $	$ \frac{10}{\eta_a^2} $ 486.757 476.489	e area (λ_o) $\frac{5}{\eta_a^2}$ 500.464 486.435	$= 10\mu_s, \eta_a$ $\frac{\frac{1}{\eta_a^2}}{527.269}$ 510.538	$= \frac{2}{3}\mu_s, \beta$ $\frac{1}{5\eta_a^2}$ 538.345 526.247	$= 3) \\ \frac{\frac{1}{10\eta_a^2}}{540.078} \\ 528.852$			
$\frac{\hline \begin{matrix} v_a \\ \hline L_{t,3} \text{ (Analytical)} \\ \hline L_{t,3} \text{ (Simulation)} \\ \hline \text{Error} \end{matrix}$	$\frac{10}{\eta_a^2}$ 486.757 476.489 2.1095%	e area (λ_o) $\frac{\frac{5}{\eta_a^2}}{500.464}$ $\frac{486.435}{2.8032\%}$	$= 10\mu_s, \eta_a$ $\frac{\frac{1}{\eta_a^2}}{527.269}$ 510.538 3.1731%	$= \frac{2}{3}\mu_s, \beta$ $\frac{1}{5\eta_a^2}$ 538.345 526.247 2.2431%	$= 3)$ $\frac{\frac{1}{10\eta_a^2}}{540.078}$ 528.852 2.0786%			
	$\frac{10}{\eta_a^2}$ 486.757 476.489 2.1095% 0.993381	e area (λ_o) $\frac{5}{\eta_a^2}$ 500.464 486.435 2.8032% 1.02136	$= 10\mu_s, \eta_a$ $\frac{1}{\eta_a^2}$ 527.269 510.538 3.1731% 1.07606	$= \frac{\frac{2}{3}\mu_s, \beta}{\frac{1}{5\eta_a^2}}$ 538.345 526.247 2.2431% 1.09866	$= 3) \\ \frac{1}{10\eta_a^2} \\ 540.078 \\ 528.852 \\ 2.0786\% \\ 1.1022 \\$			
	$\frac{10}{\eta_a^2}$ 486.757 476.489 2.1095% 0.993381 0.97413	e area (λ_o) $\frac{5}{\eta_o^2}$ 500.464 486.435 2.8032% 1.02136 0.994158	$= 10\mu_s, \eta_a$ $\frac{1}{\eta_a^2}$ 527.269 510.538 3.1731% 1.07606 1.04542	$= \frac{\frac{2}{3}\mu_s, \beta}{\frac{1}{5\eta_a^2}}$ 538.345 526.247 2.2431% 1.09866 1.07624	$= 3)$ $\frac{\frac{1}{10\eta_{a}^{2}}}{540.078}$ 528.852 2.0786% 1.1022 1.08047			

simulates the user movement in a hexagonal heterogeneous network. The details of the simulation model are not described in this paper. Table I shows the comparison between the analytical and simulation results, whose details of the parameter setups are described in Section III. The table indicates that the errors between the analysis and simulation results are within 3%. It is clear that the results of the analytical model are consistent with the simulation results.

III. PERFORMANCE EVALUATION

Based on the analytical model, this section investigates the performance of the MG in terms of average load index $L_{a,n}$ and total load index $L_{t,n}$. In this paper, input parameters λ_o and η_a are normalized by μ_s . For example, if the expected session service time is $1/\mu_s = 600$ s, then $\lambda_o = 10\mu_s$ means that the expected intersession arrival time at a CA is 60 s, and $\eta_a = (2/3)\mu_s$ means that the expected CA residence time for a user is 900 s. The impacts of the input parameters are discussed as follows.

Effects of n and β on $L_{a,n}$ and $L_{t,n}$: Fig. 4 plots $L_{a,n}$ and $L_{t,n}$ against n with various β setups, where $\lambda_o = 10\mu_s$ and $\eta_a = (2/3)\mu_s$. In this figure, we consider the exponential CA residence time, i.e., $\alpha = 1$ and $v_a = 1/\eta_a^2$. In Fig. 4(a), we observe that, when $\beta > 3$, as n increases, $L_{a,n}$ decreases and approaches $1/\mu_s$. On the other hand, when $\beta \le 2$, as n increases, $L_{a,n}$ increases and approaches $1/\mu_s$. A larger n implies that the service area of an MG is larger. The user has less chance to handoff to another MG during the session, and it is more likely that the session completes before the user handoffs to another MG (i.e., $E[t_{do,n}]$ approaches to the mean of the service time of a session $1/\mu_s$). Thus, the ratio



Fig. 4. Effects of n and β on $L_{a,n}$ and $L_{t,n}$ $[\lambda_o = 10\mu_s; \eta_a = (2/3)\mu_s; v_a = 1/\eta_a^2].$

 $E[N_{o,n}]/E[N_{h,n}]$ is larger. From (18), we know that $L_{a,n}$ values are dominated by $E[t_{do,n}]$ when $E[N_{o,n}]/E[N_{h,n}]$ is larger. Since $E[t_{do,n}] \approx 1/\mu_s$ when n is larger, we have that $L_{a,n}$ approaches to $1/\mu_s$ as n increases for all cases.

Consider (27). Let

$$A = \left. \frac{df_{A_n}^*(s)}{ds} \right|_{s=0}$$

and $B = 1 - f_{A_n}^*(\mu_s)$; therefore, (27) is rewritten as

$$L_{a,n} = \frac{1}{\mu_s} + \frac{B^2}{\mu_s^3 A^2} + \frac{(2 - \beta B)B}{\mu_s^2 A}.$$
 (29)

From (9), we have $A = -E[t_{A_n}]$, and A has negative values. When n is larger, the service area of an MG is larger, and $E[t_{A_n}]$ increases. Therefore, we have the following fact.

Fact 1: A decreases as n increases.

Furthermore, in (8), since $q_{(1,0)_{n-1}}p_{k,(1,0)_{n-1},(2,0)_{n-1}}$ is smaller than one, $f_{A_n}^*(\mu_s)$ decreases and approaches to zero as n increases. Hence, the following fact holds.

Fact 2: B increases and approaches to one as *n* increases.

Applying Facts 1 and 2 into (29), we have the following fact. Fact 3: When $\beta < (2/B)(\beta \ge 2/B)$, $L_{a,n}$ is an increasing (a decreasing) function of n.

In Fig. 4, we set $\eta_a = (2/3)\mu_s$. Applying $\eta_a = (2/3)\mu_s$ to (28), we have $f_{A_1}^*(\mu_s) = 2/5$ and B = 3/5 (or 2/B = 10/3) when n = 1. From Fact 3, we observe that when $\beta = 2$ or 3, $L_{a,n}$ values increase when n changes from 1 to 2. When $n \ge 2$, B approaches to 1, and 2/B approaches to 2. Hence, as $\beta \le 2$, $L_{a,n}$ is an increasing function of n, and as $\beta > 2$, $L_{a,n}$ is a decreasing function of n.

As shown in Fig. 4(b), $L_{t,n}$ exponentially increases as n increases. This is due to the fact that as n increases (i.e., the service area of an MG becomes large), there are more new session arrivals within the service area of an MG, and the total number of sessions within an MG increases significantly. The total overhead of an MG increases.



Fig. 5. Effects of η_a on $L_{a,n}$ ($\lambda_o = 10\mu_s$; $v_a = 1/\eta_a^2$; $\beta = 3$).

Based on the phenomena in Fig. 4, we summarize that, under the parameter setups in this figure, when $\beta \leq 2$, we may set nas small as possible since $L_{a,n}$ and $L_{t,n}$ values increase as nincreases. When $\beta > 2$, because as n increases, $L_{a,n}$ decreases and approaches to $1/\mu_s$, and $L_{t,n}$ increases extremely, we may properly select n such that $L_{a,n}$ is small (i.e., the user has better chance to be successfully served by an MG). For example, when $\beta = 3$, we may set n = 7; that is, an MG service area consists of 7^6 CAs.

Effects of η_a on $L_{a,n}$: Fig. 5 studies the impacts of η_a on the setup of an MG service area, where $\lambda_o = 10\mu_s$, $v_a = 1/\eta_a^2$ (i.e., the exponential CA residence time and $\alpha = 1$), and $\beta = 3$. We observe that, for all different η_a setups, as *n* increases, $L_{a,n}$ increases, and then the transition occurs at some *n* setups. When η_a is larger, the transition occurs at the larger *n*. In this figure, we fix β . From (29) and Fact 3, we have the following fact.

Fact 4: When $B < 2/\beta$ ($B \ge 2/\beta$), $L_{a,n}$ is an increasing (a decreasing) function of n. In other words, the transition occurs at $B = 2/\beta$.

As stated in Fact 2, as n increases, B increases and approaches to one. From Facts 2 and 4, in this figure, we observe that, as n increases, $L_{a,n}$ increases and then decreases. Furthermore, from (8) and (28), the following fact holds.

Fact 5: When η_a gets larger, $f_{A_n}^*(\mu_s)$ increases, and $B = 1 - f_{A_n}^*(\mu_s)$ decreases.

From Facts 2, 4, and 5, we have the phenomenon that increasing η_a has the transition occur at the larger *n*.

The figure also shows that, when η_a is larger, $L_{a,n}$ for n = 1 is smaller. This phenomenon is resulted from the fact that, as η_a increases, the sessions more likely handoff between different MGs (i.e., $E[t_{A_n}]$ decreases), and $A = -E[t_{A_n}]$ increases. Since A increases and B decreases as η_a increases, applying (29), it follows that, as η_a gets larger, $L_{a,n}$ for n = 1 is smaller.

From the above phenomena, we conclude that, under the parameter setups in this figure, to gain better $L_{a,n}$ performance, we prefer to set n = 1 when $\eta_a \ge \mu_s$ and properly select n when $\eta_a < \mu_s$, e.g., n = 7 when $\eta_a = (2/3)\mu_s$.

Effects of λ_o on $L_{a,n}$: Fig. 6 investigates the impacts of λ_o on the $L_{a,n}$ performance, where $\eta_a = (2/3)\mu_s$, $v_a = 1/\eta_a^2$, and $\beta = 3$. Fig. 6 shows that $L_{a,n}$ is not affected by various λ_o



Fig. 6. Effects of λ_o on $L_{a,n}$ $[\eta_a = (2/3)\mu_s; v_a = 1/\eta_a^2; \beta = 3].$



Fig. 7. Effects of v_a on $L_{a,n}$ [$\lambda_o = 10\mu_s$; $\eta_a = (2/3)\mu_s$; $\beta = 3$].

setups. In (29), it is clear that $L_{a,n}$ is independent of λ_o . Hence, we observe the phenomenon.

Effects of v_a on $L_{a,n}$: Fig. 7 evaluates the effects of the variance of the CA residence time distribution on the $L_{a,n}$ performance, where we set $\lambda_o = 10\mu_s$, $\eta_a = (2/3)\mu_s$, and $\beta = 3$. Fig. 7 shows that when $v_a < 1/\eta_a^2$ (i.e., $\alpha > 1$), as *n* increases, $L_{a,n}$ decreases and approaches to $1/\mu_s$. When $v_a \ge 1/\eta_a^2$ (i.e., $\alpha \le 1$), as *n* increases, $L_{a,n}$ increases and then decreases. The transition occurs at some *n* setups. Consider (29). From Fact 2, we know that *B* has the smallest value when n = 1. From Fact 4, we have that whether $L_{a,n}$ is an increasing or decreasing function of *n* is determined by whether *B* is smaller or larger than $2/\beta$. Thus, we have the following fact.

Fact 6: If *B*'s value is larger than or equal to $2/\beta$ for n = 1, *B* is always larger than $2/\beta$ as *n* increases, and $L_{a,n}$ is a decreasing function of *n*. On the other hand, if *B*'s value is smaller than $2/\beta$ for n = 1, as *n* increases, $B \ge 2/\beta$ will occur at some *n*, and $L_{a,n}$ increases and then decreases as *n* increases.

With Fact 6, we can determine whether $L_{a,n}$ is a decreasing function of n by checking B's value for n = 1. For n = 1, we have $B = 1 - f_{A_1}^*(\mu_s)$. By applying (28), we have

$$B = 1 - \left(\frac{\alpha \eta_a}{\alpha \eta_a + \mu_s}\right)^{\alpha}, \text{ for } n = 1.$$
 (30)

In Fig. 7, we set $\eta_a = (2/3)\mu_s$. Applying the η_a setup into (30) can explain why we observe the phenomenon.

To conclude, the $L_{a,n}$ performance is highly dependent on the CA residence time distribution. To gain better $L_{a,n}$ performance, we may set n = 1 when $L_{a,n}$ for n = 1 is less than $1/\mu_s$. Otherwise, we should properly set n by carefully examining the analysis results.

IV. CONCLUSION

This paper has proposed an analytical model to investigate the performance for the application-level integration of heterogeneous wireless networks. The MG handles the content format translation and the data tunneling for users. An MG service area may consist of one or more CAs (which is the service range of a wireless network). When the service area of an MG increases, more computation overhead for the content format translation for users is introduced to an MG. On the other hand, a smaller service area of an MG results in a served user more likely being handed off between different MGs and more network resources being required to tunnel the user data. The proposed analytical model studies how to properly adjust the MG's service area so that better system performance (including average load index $L_{a,n}$ and total load index $L_{t,n}$) can be achieved. The proposed analytical model has been validated by simulation experiments. Under the parameter setups in this paper, the following phenomena have been observed, which can be provided to the network operator as a guideline in setting up the heterogeneous network.

- When β ≤ 2, we may set n = 1 (i.e., a one-layer MG service area) for better L_{a,n} and L_{t,n} performance. When β > 2, n should be carefully set up by examining the analysis results for better performance.
- The L_{a,n} performance is significantly affected by the user mobility rate. For better L_{a,n} performance, it is preferred to set n = 1 when the user mobility rate is high (i.e., η_a ≥ μ_s). When user mobility rate η_a is less than μ_s, we may check the analysis results to select a proper n value for better L_{a,n} performance.
- 3) The $L_{a,n}$ performance is independent of the new session arrival rate to a CA. The CA residence time distribution significantly affected the $L_{a,n}$ performance.

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