Mobility Modeling for Two-Tier Integrated Wireless Multimedia Networks

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Abstract

This paper presents a novel mobility modeling approach for a two-tier integrated wireless system that accommodates the system complexity represented by the residence-time correlation between different access networks. Additionally, a novel session model is presented as an adapted version of the proposed mobility model. Furthermore, we develop an analytical framework using this session model to obtain several salient performance metrics such as network utilization times and handoff rates. Simulation results demonstrate that the proposed mobility model is substantially more accurate than existing modeling techniques, and that the proposed analytical framework provide tractable performance evaluation based on the new mobility model.

1 Introduction

The service convergence of heterogeneous radio access technologies has been envisioned as a viable solution to the prevalence of multimedia application over wireless networks in the near future, in order to improve both the network resource utilization and user perceived quality-of-service. The integration of wireless local area networks (WLANs) and 3G cellular networks is an example for this approach [14, 3, 5], where the users will enjoy the complementary advantages of both networks including the universal coverage of cellular networks and the low cost and sufficient resources of WLANs wherever they are available. In an integrated model, users will transfer their utilized resources as they handoff from one access technology to another, known as vertical handoff (VHO) [15], and between access points or base stations of the same access technology, known as horizontal handoff (HHO). Valid teletraffic and mobility models are crucial for proper system design and performance evaluation of different design alternatives.

The existing modeling and analysis methods for homogeneous cellular networks are not suitable in the new heterogeneous environment. In these methods, the mobile terminal (MT) mobility is modeled by the cell residence time, defined as the duration spent by the MT within a cell. Various types of random variables are used to represent the cell residence time such as the phase-type (PH) distribution [1], Erlang distribution [9, 8], Gamma distribution [7, 8], hyper-exponential and hyper-Erlang [9], and SOHYP [12]. These models are sufficient to describe the MT mobility since the exact MT position within the cell is irrelevant. On contrary, in heterogeneous systems, this level of granularity is not adequate to characterize the MT mobility because the MT uses different access technologies within the same cell. A naive solution to model a two-tier (e.g., 3G/WLAN) heterogeneous system is extending the above methods to use independent, generally distributed random variables to represent different residence times. However, as will be shown later, this simple solution ignores the correlation between the residence times and can lead to inaccurate performance estimation results for many multimedia applications.

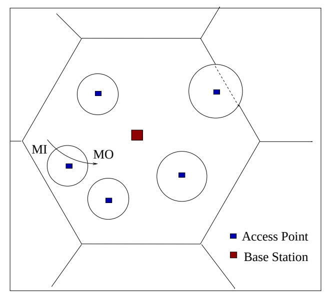

Figure 1. 3G-WLAN Integrated System

In this paper, we develop a novel model for MT mobility in an integrated two-tier heterogeneous wireless system. For the purpose of illustration, we use the integration of 3G and WLAN as an example, as shown in Fig. 1. In this model, we adopt a new approach that accommodates the correlation between cell and WLAN residence times with a *physical model* based on tier transition phases. It utilizes the available data obtained from real field measurements or topology simulation to physically represent the MT mobility rather than the simply distribution fitting used in the classical approaches. Additionally, we prove the model validity by comparing the results of simulation and analysis based on an adapted version of this mobility model, for a wide range of multimedia applications.

To the best of our knowledge, this work is the first study that addresses mobility modeling and performance analysis in an integrated heterogeneous network. We show that the proposed methods provide significantly improved accuracy in mobility modeling and performance evaluation for future wireless networks and mobile computing systems, in which multiple types of services (voice, data, and/or multimedia) will be supported over multiple access technologies.

2 Mobility Modeling

2.1 Two-Tier Mobility Model

In homogeneous systems, the collected mobility information, e.g., residence cell time measurements, is fitted to a versatile distribution such as PH, Gamma, Erlang, hyper-Erlang, or SOHYP distributions to characterize the MT mobility used in system performance analysis. A common assumption in these models is the independence between different random variables that control the system dynamics. However, in heterogeneous systems, more variables are required to model the MT mobility including WLAN, inter-WLAN, and cell residence times. On contrary to the homogeneous case, the independence of these time variables can not be assumed, since the cell residence time can be expressed as a summation of the MT's WLAN and inter-WLAN residence times within the same cell. Hence, fitting the available information about these variables independently will not result in an accurate mobility model. The proposed modeling approach considers this fact, and consequently, results in better estimation for different performance metrics using PH random variables.

Generally, a PH random variable is defined as the absorption time of an evanescent finite-state Markov process to a single absorbent state. This process can be expressed using an infinitesimal generator matrix, $\mathbf{Q}$, and an initial state distribution vector υ as follows [10]

$$\mathbf{Q} = \begin{pmatrix} \mathbf{T}_{p\times p} & \mathbf{T}^0_{p\times 1} \\ \mathbf{0}_{1\times p} & 0 \end{pmatrix}, \tag{1}$$

$$\upsilon = (\alpha_{1\times p}, \gamma_{1\times 1}). \tag{2}$$

Additionally, the corresponding PH distribution can be defined by $(\alpha, \mathbf{T})$, such that if a random variable X is $PH(\alpha, \mathbf{T})$ of order p, then its probability density function is expressed as

$$f(x) = -\alpha \exp(\mathbf{T}x)\mathbf{T}\mathbf{e}\,,\ x \geq 0\,, \tag{3}$$

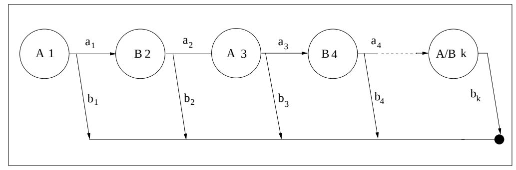

Figure 2. Mobility Model

where $\mathbf{e}$ is a column vector of dimension p with all its element equal one.

Generally, there are two different ways for modeling with PH distributions [6], a fictitious approach and a physical approach. In the former, PH distributions are used as a versatile, dense, and algorithmically tractable class of distributions defined on the non-negative real numbers; while in the latter, the phases or blocks of phases represent a real process in the system. In this paper, we used the latter approach to model MT mobility.

Without loss of generality, we assume that the MT prefers WLAN due to its larger bandwidth and lower cost. Hence, the MT will start its session in WLAN if it is available, and it will handoff to a WLAN whenever one is encountered. Therefore, the MT lifetime within the any cellular cell consists of consecutive durations spent in WLANs and in between them until it eventually exits this cell to a neighboring one. This exit may be a horizontal handoff at the cell borders or through a WLAN that overlap with more than one cell as shown in Fig. 1.

Thus, in our mobility model, we represent the cell residence time as a special type of PH random variable known as the Coxian random variable [4], whose graphical representation is shown in Fig. 2.

However, we do not simply fit the measurement to estimate the parameters of this random variable. Rather, we analogously represent the durations spent by the MT in WLANs and in between them as the duration spent by the random variable in different phases before being absorbed (exiting the cell).

In Figure 2, each phase is labelled with a letter and a number. The former represents the access technology, and the latter represents the phase sequence. The technology labels A and B may respectively represent cellular and WLAN or WLAN and cellular technologies depending on the accessed technology when the MT starts its cell visit. The MT may start its cell residence within or outside a WLAN. Whenever the MT is exiting a specific phase i, where $i = 1, 2, ..., k-1$, it exits the cell with probability b_i or continue to the next phase with probability a_i, where $a_i + b_i = 1$. We assume that the duration spent by the MT in phase A_i or B_i is exponentially distributed with mean $1/\mu_i$[1]. When the MT is in the last phase k, which

[1]More general distributions can be used. The results show that using

may be WLAN or cellular, it exits the cell with probability $b_k = 1$. In the rest of the paper, we will subdivide the phases into two subsets C and W that correspond to cellular and WLAN phases respectively.

The proposed model represent the cell residence time as a summation of the durations spent by the MT within the WLANs and in between them. Hence, it accommodates the correlation between the cell residence time and both WLAN and inter-WLAN residence times. The proposed model is an approximated one in the sense that it truncates the number of alternating VHOs to k, the Coxian distribution order. However, the obtained results show it appropriately represents the system. The model order, k, is determined from the obtained measurements such that the probability of cell exit exceeds a pre-defined probability threshold.

2.2 Model Parameter Estimation

In this subsection, we discuss how to obtain the parameters of the model shown in Fig. 2 from the collected data. The data can be obtained from field measurements or by simulation. In this work, we use the second approach since field measurements are not yet available for these systems. The following information is collected for each visited cell:

- Initial technology, defined as the access technology used by the MT when it enters the cell,
- WLAN durations, defined as the time spent by the MT in a WLAN,
- Inter-WLAN durations, defined as the time spent by the MT in between WLANs, and
- Number of WLAN boundary crossings.

The parameter estimation process will be repeated for two different models based on the two types of initial networks. Hence, the obtained data are first clustered into two separate data partitions based on the initial technology. Then, for each partition, we have

$$b_i = \frac{N_c(i-1)}{\sum_{j=i-1}^{\infty} N_c(j)} \ ,$$

where $N_c(i)$ denotes the number of cells in which exactly i VHOs are performed. Furthermore, μ_i is calculated as the inverse of the average duration spent by the MT in the corresponding physical network visit. For example $1/\mu_1$is the mean duration spent by the MT in their first visit to network A. Similarly, $1/\mu_2$ is the mean duration spent by the MT in their first visit to network B, and so on for $i = 1, 2, ..., k-2$. Finally,the last two phases parameters are calculated from the information of the remaining visits for the corresponding networks.

exponentially distributed phases provides an acceptable tradeoff between complexity and accuracy.

3 Session Model and Performance Analysis

In this section, we present a session model that can be used to analyze the performance of different applications. We study the performance within one cellular cell starting from the moment at which the MT starts using the cell resources until the session ends or handoff to a neighbor cell.

Each application S is characterized by two parameters, which are arrival rate according to a Poisson process with parameters λ_n^S, and holding times t_{ch}^S and t_{wh}^S that are exponentially distributed with parameters λ_{ch}^S and λ_{wh}^S for cellular network and WLAN respectively,

These parameters depend on the application nature; for example, conversational applications such as voice over IP (VoIP) and video conference (V-conf) are expected to preserve the same holding time and bandwidth requirement in both networks. On the other hand, streaming applications, such as video on demand (VoD) and radio on demand (RoD), are bandwidth greedy application due to their buffering capabilities. Hence, the WLAN session holding is smaller than cellular session holding time, i.e., $\lambda_{wh}^S > \lambda_{ch}^S$.

In the following, we first present the session model. We then present a framework to obtain some of the salient performance metrics.

3.1 Session Model

The session model is an adapted version of the mobility model with few modifications to the physical interpretation of each phase and the absorbing state. In the session model, each phase represents both MT activity status and the utilized access technology. Hence, a specific phase may be exited due to the exiting of the current access technology, the termination of the current session (normal or forced termination), or handoff to a neighboring cell. Consequently, different absorbing states are defined including Term state, normal session termination, SHH state, successful horizontal handoff, HHFT state, forced termination during horizontal handoff, and VHFT state, forced termination during vertical handoff.

Hence, the generator matrix of the session Markovian process will have the following structure

$$\mathbf{Q}_s = \begin{pmatrix} \mathbf{Q}_{TT} & \mathbf{Q}_{Term} & \mathbf{Q}_{SHH} & \mathbf{Q}_{HHFT} & \mathbf{Q}_{VHFT} \\ \mathbf{0} & 0 & 0 & 0 & 0 \end{pmatrix} , \tag{4}$$

where

$$\mathbf{Q}_{TT} = [q_{i,j}] = \begin{cases} -(\mu_i + \lambda_{ch}^S) & , \forall\, i = j \,,\, i \in C \\ -(\mu_i + \lambda_{wh}^S) & , \forall\, i = j \,,\, i \in W \\ a_i\mu_i & , \forall\, j = i+1 \,,\, i \in C \\ a_i\mu_i(1-P_v) & , \forall\, j = i+1 \,,\, i \in W \\ 0 & , \text{otherwise} \end{cases} , \tag{5}$$

$$\mathbf{Q}_{Term} = [q_{i,1}] = \begin{cases} \lambda^S_{ch} & ,\forall i \in C \\ \lambda^S_{wh} & ,\forall i \in W \end{cases} ,$$

$$\mathbf{Q}_{SHH} = [q_{i,1}] = \begin{cases} b_i\mu_i(1-P_h) & ,\forall i \in C \\ b_i\mu_i(1-P_v) & ,\forall i \in W \end{cases} ,$$

$$\mathbf{Q}_{HHFT} = [q_{i,1}] = \begin{cases} b_i\mu_i P_h & ,\forall i \in C \\ b_i\mu_i P_v & ,\forall i \in W \end{cases} ,$$

$$\mathbf{Q}_{VHFT} = [q_{i,1}] = \begin{cases} 0 & ,\forall i \in C \\ a_i\mu_i P_v & ,\forall i \in W \end{cases} .$$

Once the session model infinitesimal generator matrix is obtained, one can obtain different performance metrics using standard Markovian analytical techniques as shown in the next subsections.

3.2 Network Utilization Times

The utilization time of a specific network is the expected time spent by the MT in the corresponding transient state before being absorbed. This metric can be obtained by analyzing the Markovian session process dynamics determined by

$$\frac{d\,\pi(t)}{dt} = \pi(t)\mathbf{Q}_s\,, \qquad \pi(0) = \pi_{\mathbf{o}}\,, \tag{6}$$

where $\pi(t)$ represents the transient state probability vector and $\pi_{\mathbf{o}}$ represents the initial state distribution. The expected time spent in each state during interval $[0, t)$, denoted as $\mathbf{L}(t)$, can be expressed using the cumulative state probabilities and equals $\mathbf{L}(t) = \int_0^t \pi(u)du$, which can be written as [2]

$$\frac{d\mathbf{L}(t)}{dt} = \mathbf{L}(t)\mathbf{Q} + \pi(0), \qquad \mathbf{L}(0) = \mathbf{0}\,. \tag{7}$$

Thus, the time spent in each transient state before being absorbed can be obtained by taking $\lim_{t\longrightarrow\infty} \mathbf{L}_T(t)$, where $\mathbf{L}_T(t)$ is a reduced version of $\mathbf{L}(t)$ restricted to the transient states. This step is valid only for Markovian process whose initial probability is limited to the transient states as in our case. Hence, by taking the limits in (7), we have

$$\mathbf{L}_T(\infty) = -\pi_{\mathbf{T0}}\mathbf{Q}^{-1}_{TT}\,, \tag{8}$$

where $\pi_{\mathbf{T0}}$ is a reduced initial distribution vector restricted to the transient phases. For handoff sessions, this distribution will be equal to the initial state distribution of the mobility model PH distribution, i.e. , while for new sessions, it equals the initial state distribution of the residual cell residence time, $\pi_{\mathbf{T0}} = (\alpha\mathbf{T}^{-1}\mathbf{e})^{-1}\alpha\mathbf{T}^{-1}$ [10].

Consequently, the expected cellular network utilization time in the integrated model will be $L_c = \sum_{i\in C}\mathbf{L}_T(i)$ and the expected WLANs utilization time will be $L_w = \sum_{i\in W}\mathbf{L}_T(i)$. Finally, the session cell dwelling time, $L_s = L_c + L_w$.

3.3 Horizontal Handoff Rate

The handoff rate is defined as the expected number of generated handoffs from a new session. In an integrated two-tier network, the handoff rate differs from the homogeneous case due to session dynamics variations due to embedded system heterogeneity. Let P^{AB}_X denotes the absorption probability to state X given that a session of type B starts in network A. These prababilities can be obtained using standard Markovian analysis on Q_S [13]. Additionally, let P_{wo} denotes the probability that the initial network is WLAN, which equals the percentage of WLAN coverage; similarly, P_{co} denotes the probability that the initial network is the cellular network, equals $(1 - P_{wo})$. Hence, the probability that a handoff session will normally terminate within the same cell or will be blocked during vertical handoff, P_{hf}, can be expressed as $P_{hf} = P_{wo}(1 - P^{wh}_h) + P_{co}(1 - P^{ch}_h)$, where $P^{wh}_h = P^{wh}_{SHH} + P^{wh}_{HHFT}$ and $P^{ch}_h = P^{ch}_{SHH} + P^{ch}_{HHFT}$. Furthermore, the probability that a handoff session will perform exactly one successive horizontal handoff, P_{ss} can be expresses as $P_{ss} = P_{wo}(P^{wh}_{HHFT} + P^{wh}_{SHH}P_{hf}) + P_{co}(P^{ch}_{HHFT} + P^{ch}_{SHH}P_{hf})$. Consequently, one can derive the marginal distribution function of horizontal handoff number, H, assuming the session starts in a WLAN as follows

$$\begin{aligned} &P(H = 0) = P^{wn}_{Term} + P^{wn}_{VHFT}\,, \\ &P(H = 1) = P^{wn}_{HHFT} + P^{wn}_{SHH}P_{hf}\,, \\ &P(H = k) = P^{wn}_{SHH}(P_{wo}P^{wh}_{SHH} + P_{co}P^{ch}_{SHH})^{k-2}P_{ss}\,, k \geq 2 \end{aligned}$$

Hence, the expected number of horizontal handoffs for a session starting in a WLAN will be

$$\begin{aligned} E\{H|W\} &= \sum_{k=0}^{\infty} kP(H = k) \\ &= P^{wn}_{HHFT} + P^{wn}_{SHH}\left(P_{hf} + P_{ss}\left(\frac{2-x}{(1-x)^2}\right)\right) , \end{aligned}$$

where $x = P_{wo}P^{wh}_{SHH} + P_{co}P^{ch}_{SHH}$. Similarly, the handoff rate for a session starting in the cellular network is

$$E\{H|C\} = P^{cn}_{HHFT} + P^{cn}_{SHH}\left(P_{hf} + P_{ss}\left(\frac{2-x}{(1-x)^2}\right)\right) .$$

Hence, the total handoff rate, N_{HH}, equals

$$N_{HH} = E\{H|W\}P_{wo} + E\{H|C\}(1 - P_{wo})\,.$$

3.4 Vertical Handoff Rates

There are two types of vertical handoffs: upward and downward handoffs. The former is defined as the transition from a WLAN to the cellular network, and the latter is the reverse case. These two types are also known as move out

(MO) and move in (MI) respectively, as shown in Fig. 1. The latter taxonomy is based on the fact that WLAN is considered a preferred network to cellular network due to its higher bandwidth and lower cost. In this section, we derive the marginal distribution of the number of MIs and MOs from which we obtain vertical handoff rates. Similar to the horizontal handoff rate, the vertical handoff rates depend on the initial network within the cell.

We define the phase exit probability, $P_e(i)$, as the probability that the session duration is larger than the residence time of phase i. Hence,

$$P_e(i) = \begin{cases} \frac{\mu_i}{\mu_i+\lambda_{ch}} & ,\forall\, i \in C \\ \frac{\mu_i}{\mu_i+\lambda_{wh}} & ,\forall\, i \in W \end{cases} .$$

Additionally, we denote $P_{vs}(i)$ the probability of two consecutive successful vertical handoffs within the same cell assuming the MT is in phase i. This probability can be expressed as

$$P_{vs}(i) = P_e(i)a_i P_e(i+1)a_{i+1}(1-P_v)\,.$$

Using these probabilities, the distribution of the number of MIs assuming that the session start outside a WLAN can be derived as follows:

$$\begin{aligned} &P(MI=0|C) = 1 - P_e(1)a_1 \\ &P(MI=k|C) = \left[\prod_{i=1}^{2k-1} P_e(i)a_i\right](1-P_v)^{k-1}\cdot \\ &\qquad\qquad [1-P_{vs}(2k)]\,, k=1,2,...,MI_{max}\,. \end{aligned}$$

Similarly, the distribution of the number of MOs given the session start outside a WLAN can be derived as follows:

$$\begin{aligned} &P(MO=0|C) = 1 - P_e(1)a_1P_e(2)a_2 \\ &P(MO=k|C) = \left[\prod_{i=1}^{2k} P_e(i)a_i\right](1-P_v)^{k-1}\cdot \\ &\qquad\qquad [1-P_{vs}(2k+1)]\,, k=1,2,...,MI_{max}\,. \end{aligned}$$

The derivation for the distributions of the numbers of MIs and MOs, given the session starts in a WLAN phase, is similar to the above and is omitted for brevity.

Then, the MI rate N_{MI} can be calculated by

$$\begin{aligned} N_{MI} &= P_{wo}P_nE\{MI|WN\} + P_{co}P_nE\{MI|CN\} + \\ &\quad P_{wo}P_hE\{MI|WH\} + P_{co}P_hE\{MI|CH\}\,, \end{aligned}$$

where $E\{MI|AB\}$ is the expected number of MIs in a session of type B starting in network A, P_n and P_h are the probabilities that a session is a new and a handoff session respectively, and can be expressed as $P_n = \frac{1}{1+N_{HH}}$, $P_h = \frac{N_{HH}}{1+N_{HH}}$. The derivation for the MO rate, N_{MO}, is similar and is omitted. Finally, we have the vertical handoff rate $N_{MIO} = N_{MI} + N_{MO}$.

Table 1. Application Parameters

	VoIP	Vconf	RoD	VoD
$1/\lambda_{ch}$	3	30	60	90
$1/\lambda_{wh}$	3	30	10	15

4 Simulation Results

We perform simulation in Matlab to validate the analytical framework and demonstrate the superior accuracy of the proposed mobility mode in comparison with the traditional independent model.

Square cells are used for simplicity of illustration. Each cell is sub-divided into N subdivisions, where WLANs are randomly located with a certain density in the interior of a cell. The topology of WLANs in different cell are assumed to be different, so that when an MT handoffs to another cell, it experiences a new WLAN topology.

We adopt a two-dimensional Gauss-Markov movement model from [11], as it can be easily tuned to represent a wide range of user mobility patterns including both the random-walk and the constant velocity fluid-flow models. In this model, a MT velocity is assumed to be correlated in time and is modeled by a Gauss-Markov process. In its discrete version, at time n, the MT velocity in each dimension, v_n, is given by

$$v_n = \alpha_v v_{n-1} + (1-\alpha_v)\mu_v + \sqrt{1-\alpha_v^2}\, x_{n-1}\,, \qquad (9)$$

where α_v represents a past velocity memory factor such that $0 \le \alpha \le 1$, μ_v is the asymptotic mean of v_n, and x_n is an independent and stationary Gaussian process with zero mean and standard deviation σ, where σ is the asymptotic standard deviation of v_n.

The mobility parameters α_v, μ_v, and σ equal 0.9, 0.5, 0.5 respectively. additionally, the parameters for four common applications are shown in Table 1 . Additionally, WLANs are assumed to overlap with 30% of the cell area. In application simulations, the collected results represent an average of five thousand sessions.

The simulation results are compared with the analysis results for the proposed physical phase-transition model and the independent residence-time PH distribution fitting model. Figures 3-5 illustrate the cellular and WLAN network utilization times, horizontal handoff rate, and vertical handoff rate, respectively. All figures show that the proposed mobility model and analysis framework match very well with simulation, usually with less than 10% discrepancy. In comparison, the independent residence-time model can lead to 45% discrepancy, especially in estimating the vertical handoff rate for high-demand applications such as video-on-demand.

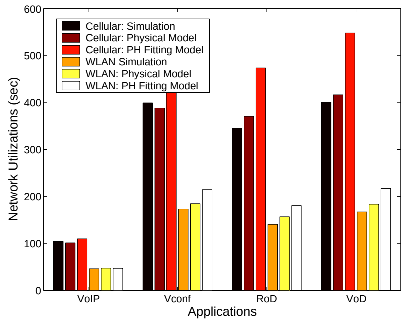

Figure 3. Network Utilization

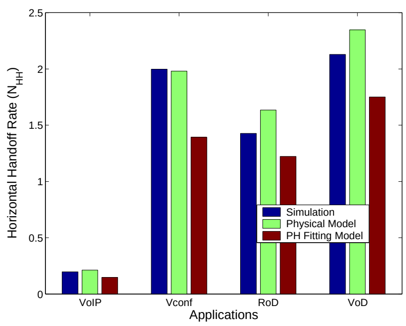

Figure 4. Horizontal Handoff Rate

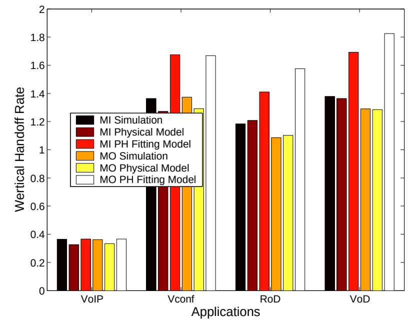

Figure 5. Vertical Handoff Rate

5 Conclusion

The integration of heterogeneous wireless access networks is envisioned as a feasible solution to the tremendous resource demand by wireless multimedia applications. This integration process requires proper mobility and traffic models to allow investigation into the effectiveness of different designs. In this paper, we develop a novel physical phase-based mobility model for an integrated two-tier system consisting of 3G and WLAN access technologies, which accommodates the correlation between the residence times in different tiers. Additionally, we develop a new session model and use it to obtain several performance metrics including network utilization times and horizontal and vertical handoff rate. Simulation and analysis results demonstrate that the proposed model is mathematically tractable, while significantly outperforming the traditional independent residence-time models for a wide range of multimedia applications.

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