Modeling and Performance Analysis of Beyond 3G Integrated Wireless Networks

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***Abstract*— Next-generation wireless networking is evolving towards a multi-service heterogeneous paradigm that converges different pervasive access technologies and provides a large set of novel revenue generating applications. Hence, system complexity increases due to its embedded heterogeneity, which can not be accounted by the existing modeling and performance evaluation techniques. Consequently, the development of new modeling approaches becomes as a crucial requirement for proper system design and performance evaluation. This paper presents a novel mobility model for a two-tier integrated wireless system using a new modeling approach that accommodates the aforementioned complexity. Additionally, a novel session model is developed as an adapted version of the proposed mobility model. These models use phase-type distributions that are known to approximate any generic probability laws. Using the proposed session model, a novel generic analytical framework is developed to obtain several salient performance metrics such as network utilization times and handoff rates. Simulation and analysis results prove the proposed model validity and demonstrate the accuracy of the novel modeling approach when compared with traditional modeling techniques.**

I. INTRODUCTION

The future wireless networking is envisioned as an integrated system of heterogeneous pervasive wireless access technologies that provides its users with a diverse set of applications. The integration of wireless local area networks (WLANs) and third-generation (3G) cellular networks [1], [2], [3] is an example of this networking paradigm in which users will enjoy the complementary advantages of both networks including the universal coverage of cellular networks and the low cost and large bandwidth of WLANs. In such heterogeneous system, the mobility influence on network performance will be strengthened due to the user ability to roam from one technology to another, known as vertical handoff (VHO) [4], in addition to the traditional cellular horizontal handoff (HHO). This VHO greatly impacts both session dynamics and system resource utilization [5]. Hence, developing novel models that accommodate these details becomes a crucial requirement for proper system design and performance evaluation of different design alternatives.

In homogeneous networks, the mobile terminal (MT) mobility is modeled by its cell residence time (CRT), defined as the duration spent by the MT within a cell. Various types of random variables are used to represent the CRT such as the phase-type (PH) distribution [6], Erlang distribution [7], [8], hyper-exponential and hyper-Erlang [8], Gamma distribution [7], [9], and SOHYP [10]. These models are sufficient to describe the MT mobility in homogeneous networks since the exact MT position within the cell is irrelevant. On contrary, in heterogeneous networks, the MT location within the cell is important since the MT can use different access technologies within the cell to receive different levels of quality of service (QoS). Hence, the MT mobility can not be uniquely described by the CRT due to VHO transitions within the overlay network cells. Consequently, more parameters are required such as WLAN and inter-WLAN residence times to accurately represent all mobility details. In this context, the WLAN residence time is similar to the CRT for the 3G cell, while the inter-WLAN residence time is defined as the duration spent by the MT in the cellular network between consecutive WLAN visits.

In this paper, we develop a novel model for MT mobility in an integrated two-tier heterogeneous wireless system. In this model, we adopt a new modelling approach that accommodates the correlation between different residence times, which can not be realized by extending traditional models assuming generally but independently distributed time variables. The key idea of the new model is to represent the 3G CRT as a summation of WLAN and inter-WLAN residence times. Additionally, we develop a session model based on the proposed mobility model for data and multimedia applications in next-generation wireless networks. Furthermore, using this session model, we develop a performance evaluation framework to derive several salient performance metrics such as network utilization times and handoff rates. The proposed modeling approach provides significant accuracy in evaluating the performance of future multi-service heterogeneous mobile systems.

The rest of this paper is organized as follows. In Section II, we present the new mobility model. The subsequent session model and the analytical performance framework are presented in Section III. Section IV presents the results that show the validity of the proposed models. Finally, conclusions are presented in Section V.

II. MOBILITY MODELING

In heterogeneous systems, as the MT traverse the overlay cell, it may associate itself with one or more different access technologies as shown in Fig. 1 (e.g. T3 and T2 respectively). Additionally, the MT may start its overlay cell visit in either

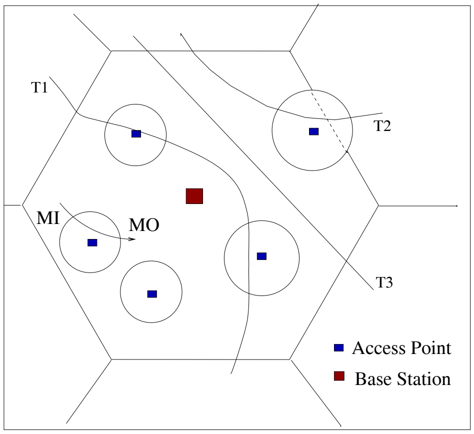

Fig. 1. 3G-WLAN Integrated System

technology as shown in T1 and T2. Generally, technology transitions determine the bounds of each access technology visit, while the CRT is bounded by HHOs. Clearly, the CRT comprises a sequence of stages represented by durations spent by the MT in different technologies and bounded by MT technology transitions.

Our proposed mobility model is inspired by the similarity between the operational phases of PH distributions and the sequential stages of the MT CRT. 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 represented by an infinitesimal generator matrix, $\mathbf{Q}$, and an initial state distribution vector υ as follows [11]

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

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

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

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

where $\mathbf{e}$ is a column vector of dimension p with all its elements equal one. Generally, there are two different modeling approaches with PH distributions [12]: fictitious and physical approaches. 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, phases or blocks of phases represent physical processes in the model. The fictitious approach has been successfully used to model the CRT in homogeneous network, but it can not be used to model heterogeneous network due to the characteristic diversity of different access networks. Hence, the second approach should be considered in the new model. In addition to the modelling approach change, the common independence assumption of different time variables is no longer valid and their correlation should be considered

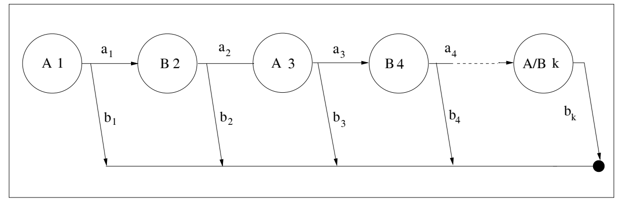

Fig. 2. Mobility Model

in the new model. The proposed model considers both issues as shown in the following subsection.

A. A CRT Model for Two-Tier Integrated Wireless Networks

Fig. 2 shows the proposed CRT model structure for two-tier integrated wireless networks, such as a 3G-WLAN integrated system, with k stages representing consecutive visits of networks A and B. Each stage is labelled with a letter that represents the access technology and a number representing the stage sequence. It is worth mentioning that A and B may either denote WLAN and cellular network respectively or vise versa depending on the initial technology visited by the MT upon session initiation or cellular handoff. Generally, the duration spent by the MT in stage A_i or B_i is assumed to be $PH(\alpha_i, \mathbf{T}_i)$ whose absorption corresponds to an access technology transition. Upon exiting a specific stage i, where $i = 1, 2, ..., k-1$, the MT may exit the cell with probability b_i or may continue to the next phase $i+1$ with probability a_i, where $a_i + b_i = 1$. In the last stage k, which may be WLAN or cellular, the MT exits the cell with probability $b_k = 1$.

Clearly, using this model the CRT is expressed as a summation of the durations spent by the MT within the WLANs and in between them. Hence, the proposed model accommodates the correlation between the CRT and both WLAN and inter-WLAN residence times. The resultant CRT will be PH due to the closure property of PH distributions under specific operations such as summation [11], and is denoted as $PH(\alpha_m, \mathbf{T}_m)$

$$\mathbf{T}_m = \begin{pmatrix} \mathbf{T}_1 & a_1\mathbf{t}_1\alpha_2 & \mathbf{0}... & ..\mathbf{0} \\ \mathbf{0} & \mathbf{T}_2 & a_2\mathbf{t}_2\alpha_2 & ..\mathbf{0} \\ . & & . & . \\ \mathbf{0}.. & & \mathbf{0} & \mathbf{T}_k \end{pmatrix} \tag{4}$$

$$\alpha_m = [\alpha_1\ \mathbf{0}] \tag{5}$$

where $\mathbf{t}_i = -\mathbf{T}_i\mathbf{e}$. It is worth mentioning that, if the stage residence times are exponentially distributed, this distribution is equivalent to the Coxian distribution [13]. Hence, we identify the models with exponentially and PH distributed stages as *Coxian* and *extended-Coxian* models respectively. It is worth mentioning that the proposed models are approximated in the sense that the number of alternating WLAN-cellular visits is truncated to a specific value k while it can go indefinitely. This value is determined from the obtained measurements such that the probability of cell exit exceeds a pre-defined probability threshold. Additionally, in the rest of the paper, we will subdivide the phases into two subsets C and W that correspond to cellular and WLAN stages respectively[1].

B. Model Parameter Estimation

The proposed model parameters are estimated from MT mobility traces that can be obtained from direct field measurements or by simulation. In Section IV, we follow the second approach since real measurements are not yet available for next-generation 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 obtained data are first clustered into two separate data partitions based on the initial technology. Then, for each partition, we calculate b_i as

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

where $N_c(i)$ denotes the number of cells in which exactly i VHOs are performed. Furthermore, the PH distribution parameters of each stage are estimated using distribution fitting tools such as the EMpht package [14] to statistically represent the duration spent by the MT in the corresponding physical network visit. For example α_1 and T_1 are calculated from the measurement corresponding to the MT's first visit to network A. Similarly, α_2 and T_2 are calculated from the measurements corresponding to the MT's 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. As an example, let cv_i denote the coefficient of variation of stage i measurements, defined as $cv_i = \frac{\sigma_i}{\mu_i}$, where σ_i and μ_i represent the standard deviation and mean of stage i measurements respectively. Based on the cv_i value, stage i measurements may be fitted to [13]

- hyper-exponential distribution if $cv_i > 1$,
- exponential distribution if $cv_i = 1$, or
- hypo-exponential (generalized Erlang) distribution if $cv_i < 1$.

III. Session Model and Performance Analysis

The proposed session model is an adapted version of the aforementioned mobility model. In this session model each provided service S is characterized by two parameters: a Poissonian arrival rate with parameters λ_n^S and exponentially distributed session holding times t_{ch}^S and t_{wh}^S 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 applications due to their buffering capabilities.

Additionally, we develop a generic performance analysis framework to calculate different salient performance metrics for different applications. Without loss of generality, we assume that active MTs always handoff to a WLAN when it is encountered due to its larger bandwidth and lower cost. 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 the MT hands-off to a neighbor cell. In the following subsections, we first present the session model and then present the performance analysis framework.

A. Session Model

In the session model, the PH phases represent both MT activity status and the utilized access technology. Hence phase transitions occur due to new access technology availability, current access technology exiting, current session termination (normal or forced termination), or handoff to a neighboring cell. Hence, different absorbing states are defined as follows

- Term state, normal session termination,
- SHH state, successful HHO,
- HHFT state, forced termination during HHO, and
- VHFT state, forced termination during VHO.

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

$$\mathbf{Q}_S = \begin{pmatrix} \mathbf{Q}_{TT} & \mathbf{Q}_{Term} & \mathbf{Q}_{SHH} & \mathbf{Q}_{HHFT} & \mathbf{Q}_{VHFT} \\ \mathbf{0} & 0 & 0 & 0 & 0 \end{pmatrix}, \tag{6}$$

where

$$\mathbf{Q}_{TT} = [\mathbf{M}_{ij}] = \begin{cases} T_i - \lambda_{ch}^S I & \forall\, i = j \,,\, i \in C \\ T_i - \lambda_{wh}^S I & \forall\, i = j \,,\, i \in W \\ a_i \mathbf{t}_i \alpha_j & \forall\, j = i+1 \,,\, i \in C \\ (1 - P_{vb}) a_i \mathbf{t}_i \alpha_j & \forall\, j = i+1 \,,\, i \in W \\ 0 & \text{otherwise} \end{cases}, \tag{7}$$

$$\mathbf{Q}_{Term} = [\mathbf{q}_{i,1}] = \begin{cases} \lambda_{ch}^S \mathbf{e} & \forall\, i \in C \\ \lambda_{wh}^S \mathbf{e} & \forall\, i \in W \end{cases},$$

$$\mathbf{Q}_{SHH} = [\mathbf{q}_{i,1}] = \begin{cases} b_i \mathbf{t}_i (1 - P_{hb}) & \forall\, i \in C \\ b_i \mathbf{t}_i (1 - P_{vb}) & \forall\, i \in W \end{cases},$$

$$\mathbf{Q}_{HHFT} = [\mathbf{q}_{i,1}] = \begin{cases} b_i \mathbf{t}_i P_{hb} & \forall\, i \in C \\ b_i \mathbf{t}_i P_{vb} & \forall\, i \in W \end{cases},$$

$$\mathbf{Q}_{VHFT} = [\mathbf{q}_{i,1}] = \begin{cases} 0 & \forall\, i \in C \\ a_i \mathbf{t}_i P_{vb} & \forall\, i \in W \end{cases},$$

where P_{vb} and P_{hb} represent the VHO and HHO blocking probabilities, and I is the identity matrix. It is worth mentioning that by aggregating the absorption states, the session Markovian process can be expressed as $PH(\alpha_m, \mathbf{Q}_{TT})$. Using the session model infinitesimal generator matrix, one can

[1]As a notational remark, we will be using subscripts c and w to denote cellular network and WLAN parameters respectively. Additionally, we will denote all vectors using boldface. Furthermore, we will use i and j as stage indexes and r and s as phase indexes.

obtain different performance metrics as shown in the next subsections.

B. Initial State Distribution

The initial state distribution, π_{To}, represents the probability distribution for starting the session in a specific phase and mainly depends on the session type: handoff or new session. For handoff sessions, the initial state distribution will be equal to the CRT initial state distribution, i.e. $\pi_{To} = \alpha_m$, while for new calls, it equals the residual CRT initial state distribution. Since the residual time of any PH distribution $PH(\alpha, \mathbf{T})$ is another PH distribution $PH(\beta, \mathbf{T})$ such that $\beta = (\alpha \mathbf{T}^{-1}\mathbf{e})^{-1}\alpha\mathbf{T}^{-1}$ [11], we have $\pi_{\mathbf{To}} = (\alpha_m \mathbf{T}_m^{-1}\mathbf{e})^{-1}\alpha_m\mathbf{T}_m^{-1}$ for new sessions.

C. Session Termination Probabilities

The session termination probabilities equal the absorption probabilities of the Markovian session process and are estimated using an embedded Markov chain probability transition matrix, $\mathbf{W} = [w_{ij}]$. The matrix $\mathbf{W}$ can be derived from the infinitesimal generator matrix $\mathbf{Q}_S$ [15]. Similarly to $\mathbf{Q}_S$, $\mathbf{W}$ can be partitioned to transient and absorbing states such that

$$\mathbf{W} = \begin{pmatrix} \mathbf{W}_{TT} & \mathbf{W}_{Term} & \mathbf{W}_{SHH} & \mathbf{W}_{HHFT} & \mathbf{W}_{VHFT} \\ \mathbf{0} & e_1 & e_2 & e_3 & e_4 \end{pmatrix},$$

where e_i is an all zero column vector except at the i^{th} location, which is equal to one. Consequently, the absorption probability to a specific state X can be calculated as [15]

$$P_X = \pi_{To}(I - \mathbf{W}_{TT})^{-1}\mathbf{W}_X\,, \tag{8}$$

where X can be Term, SHH, HHFT, or VHFT. These absorption probabilities can be used to calculate several performance metrics as shown in the following subsections.

D. Session Probabilities

In homogeneous networks, session probabilities mainly depends on the session type, B, which can be either a new or a handoff session, while in heterogeneous networks, these probabilities additionally depends on the initial network, A, which may be either a cellular network or a WLAN. The initial network determines the mobility model, and consequently the session model, whose parameters are determined from the corresponding data partition. In the mean time, the session type determines the initial phase distribution π_{To} as presented in subsection III-B.

The initial network probabilities depend on the WLAN coverage area, assuming that the user will always use WLAN whenever it is available. Therefore, the probability that the initial network is a WLAN equals to the percentage of WLAN coverage, P_{wo}, and the probability that the initial network is the cellular network, $P_{co} = (1 - P_{wo})$. On the other hand, session-type probabilities depend on the application HHO rate, N_{HH}, defined as the expected number of induced HHOs from a new session. The probability that a session is a new one, P_n, equals [9]

$$P_n = \frac{1}{1 + N_{HH}}\,,$$

while the probability that the arrived session is a handoff session, will be $P_h = 1 - P_n$.

E. Horizontal Handoff Rate

In an integrated two-tier network, the handoff rate generally differs from the homogeneous case due to session dynamics variations resulting from the embedded network heterogeneity. Let P_X^{AB} denotes the absorption probability to state X given that a session of type B, where $B \in \{n, h\}$, starts in network A, where $A \in \{c, w\}$. Let P_{hf} denote the probability that a handoff session normally terminates within the same cell or will be blocked during VHO. Then, $P_{hf} = P_{wo}(1 - P_{SHH}^{wh} - P_{HHFT}^{wh}) + P_{co}(1 - P_{SHH}^{ch} - P_{HHFT}^{ch})$. Let P_{ss} denote the probability that a handoff session will perform exactly one successive HHO. Then, $P_{ss} = P_{wo}(P_{HHFT}^{wh} + P_{SHH}^{wh}P_{hf}) + P_{co}(P_{HHFT}^{ch} + P_{SHH}^{ch}P_{hf})$. Consequently, one can derive the marginal distribution function of the HHO number, H, assuming the session starts in network A as follows:

$$P(H = 0|A) = P_{Term}^{An} + P_{VHFT}^{An}\,,$$
$$P(H = 1|A) = P_{HHFT}^{An} + P_{SHH}^{An}P_{hf}\,,$$
$$P(H = k|A) = P_{SHH}^{An}(P_{wo}P_{SHH}^{wh} + P_{co}P_{SHH}^{ch})^{k-2}P_{ss}\,, \forall k \geq 2\,.$$

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

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

where $P_{hh} = P_{wo}P_{SHH}^{wh} + P_{co}P_{SHH}^{ch}$. Hence, the total handoff rate, N_{HH}, equals

$$N_{HH} = E\{H|W\}P_{wo} + E\{H|C\}P_{co}\,.$$

F. Network Utilization Times

The network utilization time is defined as the expected time spent by the MT using a network within the 3G cell under consideration. In our model, this metric is calculated as the duration spent by the MT in a specific type of network phases before absorption, e.g. the WLAN utilization time is estimated as the duration spent in WLAN phases before absorption. From [11], the expected total time spent in phase s until absorption, given that the initial phase is r, is given by $(-Q_{TT}^{-1})_{rs}$. Hence, the expected time spent in different phases until absorption, $\mathbf{L}_T$, can be expressed as

$$\mathbf{L}_T = -\pi_{To}\mathbf{Q}_{TT}^{-1}\,. \tag{9}$$

Consequently, given a session of type B starts in network A, the expected cellular network utilization time in the integrated model is $E\{L_c|AB\} = \sum_{r\in C}\mathbf{L}_T(r)$ and the expected WLANs utilization time is $E\{L_w|AB\} = \sum_{r\in W}\mathbf{L}_T(r)$. Hence, the expected cellular utilization time is expressed as

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

Similarly, the expected WLAN utilization time can be estimated. Finally, the expected session cell dwelling time, $E\{L_s\} = E\{L_c\} + E\{L_w\}$.

G. Vertical Handoff Rates

The VHO rate is defined as the expected number of VHOs induced by an active session within a 3G cell. Generally, two types of VHOs are defined: upward and downward VHOs, also respectively known as move out (MO) and move in (MI) depending on the direction of motion with respect to WLANs. The VHO rates are calculated for different session cases using Markovian reward models [16]. For example, the MI rate is calculated by assigning any phase $s \in C$ a reward equaling the summation of the transition rates from phase s to any phase $l \in W$, i.e. $\rho_s = \sum_{l \in W} q_{sl}$, where q_{sl} is the transition rate from phase s to phase l in $\mathbf{Q}_S$. Then, the accumulated reward until absorption for a specific phase s can be calculated as the product of the assigned phase reward and the duration spent within this phase $(-Q_{TT}^{-1})_{rs}$, given that the session starts in phase r. Hence, the total expected number of MIs given that the session starts in phase r can be expressed as $\psi_r^{MI} = \sum_{s \in C} (-Q_{TT}^{-1})_{rs} \rho_s$. Consequently, the expected number of MIs, $E\{N_{MI}\}$, is expressed as

$$E\{N_{MI}\} = \pi_{To} \Psi^{MI} ,$$

where Ψ^{MI} is a column vector whose r^{th} element is ψ_r^{MI}. This procedure is repeated for different session cases, and the total MI rate, N_{MI}, can then be calculated as

$$\begin{aligned} N_{MI} &= P_{wo} P_n E\{MI|WN\} + P_{co} P_n E\{MI|CN\} + \\ &\quad P_{wo} P_h E\{MI|WH\} + P_{co} P_h E\{MI|CH\} \ . \end{aligned}$$

Using a similar reward structure, the MO rate, N_{MO}, can be obtained. Finally, we have the VHO rate $N_{VHO} = N_{MI} + N_{MO}$.

It is worth mentioning that the presented analytical framework represents a generic analytical approach that can be applied to any PH system representation to obtain the derived performance metrics, including the classical distribution fitting approach.

IV. Simulation Results

We perform simulation in Matlab to validate the analytical framework and demonstrate the improved accuracy of the proposed mobility model in comparison with the traditional independent models. Square cells are used for simplicity of illustration. Each 3G cell is sub-divided into N subdivisions, where WLANs are randomly located with a certain density in the interior of a cell, each covering one subdivision. Hence, the MT encounters different topology when it handoffs to another cell. We adopt a two-dimensional Gauss-Markov movement model from [17] due to its tunability to a wide range of user mobility patterns including both the random-walk and the constant velocity fluid-flow models. In this model, the MT velocity is 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

TABLE I

Application Parameters

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

$$v_n = \alpha_v v_{n-1} + (1 - \alpha_v)\mu_v + \sqrt{1 - \alpha_v^2}\, x_{n-1} \, , \qquad (10)$$

where α_v represents a past velocity memory factor such that $0 \le \alpha_v \le 1$, 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_v, where σ_v is the asymptotic standard deviation of v_n. In the example system presented here, the mobility parameters α_v, μ_v, and σ_v are set to 0.9, 1, 0.5 respectively. Additionally, WLANs are assumed to overlap with 30% of the cell area.

We consider different applications including both symmetric-conversational applications such as VoIP and Vconf, and asymmetric-streaming applications such as RoD and VoD. The application parameters used in our simulations are shown in Table I . In session simulations, the collected results represent an average of five thousand sessions in which both P_{vb} and P_{hb} equal 0.01.

The simulation results are compared with the analysis results for the extended-Coxian, Coxian, and traditional independent PH fitting models. In the latter model, the residence times are fitted to suitable PH distributions following the same rules used for stage measurements fitting in the extended-Coxian model. Figures 3-5 illustrate the cellular and WLAN network utilization times, HHO rate, and VHO rate, respectively.

All figures show that the analytical results of the Coxian models match very well with simulation, usually with less than 10% discrepancy. In comparison, the classical generic fitting model can result in up to 65% discrepancy, especially in estimating the HHO rate for conversational applications such as video-conferencing. Clearly, ignoring the dependence of CRT and WLAN and inter-WLAN residence time result in an inaccurate estimation for the obtained metrics as shown in the figures.

Additionally, we observe that the difference between Coxian and extended-Coxian modeling is insignificant. Hence, we can model stage residence times as negative exponential random variables, which can significantly reduce the computation complexity and reduce the fitting time for real-time performance optimization sacrificing only slightly on the accuracy.

V. Conclusion

Wireless technologies are evolving towards a multi-service heterogeneous networking paradigm. Hence, the development of new mobility and traffic models emerges as a crucial requirement for proper system design and performance evaluation. In this paper, we have developed a novel mobility model for an integrated two-tier system, using the 3G-WLAN integration as an example, which accommodates the correlation

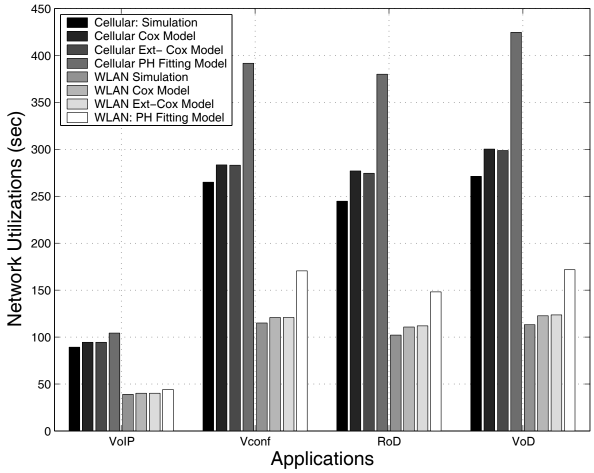

Fig. 3. Network Utilization

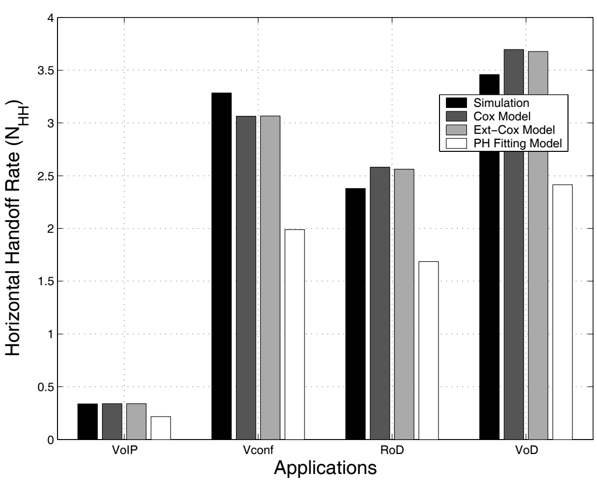

Fig. 4. HHO Rate

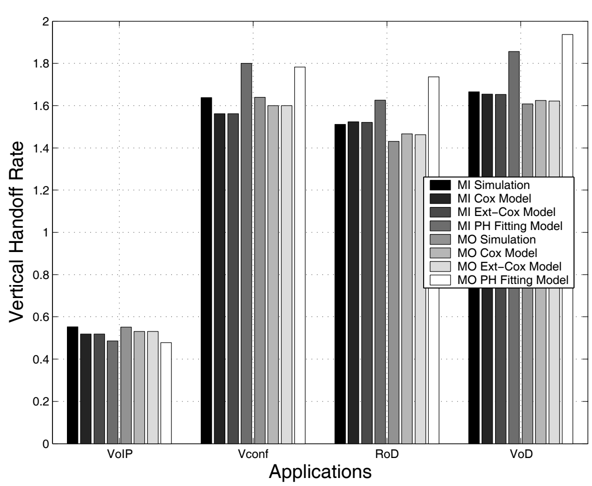

Fig. 5. Vertical Handoff Rate

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 VHO rates. Simulation and analysis results demonstrate that the proposed model significantly outperforms the traditional independent residence-time model for a wide range of multimedia applications.

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