Mobility Modeling and Analytical Solution for Spatial Traffic Distribution in Wireless Multimedia Networks

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***Abstract*—In this paper, we propose a general mobility model suitable for wireless multimedia networks. Our model is based on splitting a region into subregions. Furthermore, we make an analogy between subregions as well as their inter-connections with a multi-class Jackson queueing network comprising of infinite-server nodes. The main attribute of such a network is due to its product-form stationary distribution. Using this model, we are able to obtain a closed analytical form for the spatial traffic distribution corresponding to a specific number of network-connected users with different classes of service and mobility in a typical region. Also, we show the flexibility obtained by the proposed mobility model in representing some general distributions such as sum-of-hyper-exponentials (SOHYP), hyper-Erlang and Cox which were previously suggested to model mobility-related statistical parameters, e.g., cell dwell time and channel holding time. Finally, we apply the proposed model to a few mobility scenarios and obtain the resultant active user's location density.**

***Index Terms*—Cell dwell time, channel holding time, location density, mobility model, product-form solution, queueing network, spatial traffic distribution.**

I. Introduction

In general, there may be different spatial traffic distributions for users in the wireless networks. However, one of the great limitations of wireless networks is due to finite capacity, because of scarcity of the radio resources. Therefore, efficient use of limited radio resources is of utmost concern and challenge in designing optimum schemes for different network functions such as paging, registration, network planning, channel assignment, admission control policies, interference control, traffic engineering, etc. Succinctly, to use the radio resources efficiently, we need to disseminate the resources proportional to spatial traffic distribution in the network.

Third generation cellular mobile communication network is a good example of a wireless multimedia network. Among the most important standards in this respect is universal mobile telecommunication system, UMTS, based on wideband code-division multiple-access (W-CDMA) technique. In CDMA cellular networks, interference is crucial in both static capacity, i.e., in the case of equally loaded cells without considering mobility and handoff, and dynamic capacity, i.e., considering time-varying attribute of traffic load including mobile and handoff users. In general, interference is made of two components, intra-cell and inter-cell ([1]–[4]). One of the effective factors in inter-cell interference is the dynamic and varying location of the users, which is equivalent to spatial traffic distribution in the neighboring cells ([5], [6]).

With respect to the above discussions, analytical and closed form solution for spatial traffic distribution or users' location density would be an effective factor in calculating other aspects of wireless multimedia networks. In this respect, mobility is one of the main parameters. But, up until now, a closed analytical relationship between mobility and user's location density has not been addressed in the literature. However, a few mobility models have been proposed that are especially suitable for simulation ([7]–[9]). Also, some of the previous research works have focused on mobility-related statistical parameters in cellular networks, such as cell dwell time and channel holding time ([10]–[13]). Furthermore, a few other works consider user's location density but not mobility patterns in their analysis and, for the most part uniform location density has been considered ([1]–[3]).

In this paper, we propose a general mobility model and obtain an analytical relationship between the proposed model and spatial traffic distribution in a typical region. The concerned region can be a cell, a subregion of one cell, or several cells comprising a location area. This depends on the application overlaid on this approach, such as computation of inter-cell interference corresponding to users in connected-mode, paging or registration of the users in idle-mode [14], etc. Also we assume that the concerned users in that region are not dropped or blocked with network-state-dependent probabilities during their movements. Furthermore, we consider different mobility classes in the proposed mobility model. By applying some analogies, we map this model on an open multi-class Jackson queueing network with infinite-server nodes. The main advantage of such a network is the product-form solution for its stationary distribution. Then, we focus on the spatial traffic distribution for a fixed number of users in connected-mode introduced as active users in this paper. We consider mobility and service time requirements for active users in a typical region of the network. Also, we consider the statistical spatial arrival pattern for new and handoff active users in that region. In order to compute spatial traffic distribution, we apply some modifications on the proposed mobility model and map it to a corresponding closed queueing network. Following that, we justify the generality and

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flexibility of the proposed model regarding some general distributions previously proposed to represent the statistical behavior of the mobility-related parameters, such as sum-of-hyper-exponentials (SOHYP) ([11], [12]), hyper-Erlang [13] and Cox [15] distributions. Finally, in this paper we consider some mobility scenarios and apply our mobility model to find the active user's location density.

Following this introduction, we propose our new mobility model in Section II. We obtain analytical form for spatial traffic distribution in Section III. Section IV justifies the generality and flexibility of the proposed model. We present the application of the mobility model, using few examples, in Section V. Section VI concludes the paper.

II. Proposed New Mobility Model

Mobility is a process that is independent of the relation between users and the cellular communication network. In other words, neglecting the status of a typical user in view of being in idle-mode or connected-mode, that user has a particular and dedicated mobility pattern. Several network-independent factors affect the mobility pattern of the users. They include street characteristics (width, one-way or two-way, etc.), different obstacles existed in the streets (stop signs, stop lights, etc.), the city structure in view of the concentration of large shops, commercial centers and buildings and driving habits in that region. Some of these factors are meaningless for some types of users, for example, one-way or two-way attributes of the streets for pedestrians. In fact, we have several mobility classes for various users such that all users of the same class have similar statistical mobility pattern. A general mobility model should be able to represent different mobility classes for a wide range of users. On the other hand, such a model should be flexible in order to represent a broad range of statistical mobility patterns with high accuracy. Such a model should preferably depend on some finite, basic and simple parameters.

Our proposed mobility model is based on region splitting and treating each splitted region or subregion as an independent serving node. The resulting nodes as well as their interactions form a queueing network. We assume that users in the designated region are equivalent to customers in the queueing network. And each subregion is equivalent to a serving node in the queueing network and the dwell time of a user in each subregion is equivalent to the service time of a customer in the corresponding node. Also, leaving one subregion and entering another is equivalent to departure of a customer from the corresponding node and routing to another node. Fig. 1 shows a typical method of region splitting. For the sake of simplicity an integer number of similar subregions are considered. In Fig. 1, we indicate each subregion by a number such that the first digit from the left identifies the layer corresponding to that subregion with respect to central subregion (#11). The remaining digits indicate the number of the concerned subregion in the respective layer. The subregions in layers L_1, L_2 and L_3 are inner subregions, i.e., they do not have any boundary edge. However, the subregions in layers L_4 and L_5 are boundary subregions. The hexagonal tiling has been selected for simplicity and flexibility. Increasing the number of tiles increases the accuracy of

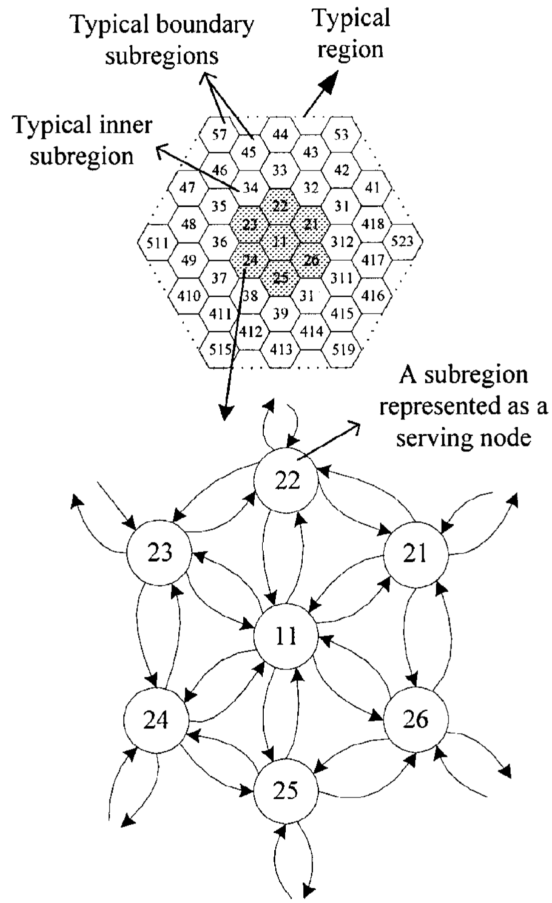

Fig. 1. Typical region splitting and equivalent queueing network.

the resulted mobility model due to more spatial resolution. We will observe that the number of equations in our model, which need to be solved, is linearly proportional to the number of subregions.

Using the above analogy, we are able to employ the characteristics of the respective queueing network to obtain its stationary probability distribution. Each state of the network is a vector that denotes the number of customers of each class at each node. We assume that we have N nodes corresponding to N subregions and I classes of customers corresponding to users' mobility classes. We have the following reasonable assumptions in the concerned queueing network [16]:

$$\sum_{k=1}^{N}\sum_{v=1}^{I}(r_{ju,kv})+r_{ju,0}=1;\ j=1,\ldots,N;\ u=1,\ldots,I \quad (1)$$

where $r_{ju,kv}$ denotes the routing probability of a class-u customer from node j to node k as a class-v customer and $r_{ju,0}$ denotes routing probability of a class-u customer from node j to the outside of the network. As we observe, we may have class-type conversion during routing, suitable for cases such as getting on or off as a passenger. We consider Markovian property for the routings [16]. Node zero in the above relation represents the exogenous world, i.e., the world outside the queueing network. With respect to our analogy, a customer takes service from a node as soon as it enters that node. Thus, each node in the concerned queueing network is an infinite-server node, such that there is not any blocking or buffering at each node. With respect to the above properties the concerned queueing network is a multi-class open Jackson network. And since, in the concerned queueing network, we have symmetric nodes with respect to arrivals and departures, we may consider arbitrary service time requirement at each node instead of negative exponential distribution as discussed in [16]. Furthermore, we require only the mean of the service time distribution at each node, in the related equations. In such a queueing network, we may find the stationary distribution by the following theorem known as Jackson's theorem.

1) Jackson's Theorem [16]: The stationary distribution $\pi(\mathbf{n})$ of the multi-class Jackson network equals:

$$\pi(\mathbf{n}) = \prod_{j=1}^{N} \pi_j(\mathbf{n}_j) \tag{2}$$

where $\mathbf{n} = (\mathbf{n}_1, \mathbf{n}_2, \ldots, \mathbf{n}_N)$, $\mathbf{n}_j = (\mathbf{n}_{j1}, \mathbf{n}_{j2}, \ldots, \mathbf{n}_{jI})$ and

$$\pi_j(\mathbf{n}_j) = b_j^{-1} \prod_{u=1}^{I} \left(\frac{\alpha_{ju}}{\mu_{ju}}\right)^{n_{ju}} \frac{1}{n_{ju}!} \tag{3}$$

where n_{ju} is the number of class-u customers at node j, μ_{ju} is the departure rate of class-u customers from node j and α_{ju} is the arrival rate of class-u customers at node j. Moreover, the probability that node j contains n customers of all classes equals:

$$b_j^{-1} \frac{\rho_j^n}{n!} \tag{4}$$

where b_j is a normalization constant, equal to:

$$b_j = \sum_{n=0}^{\infty} \frac{\rho_j^n}{n!} \tag{5}$$

and ρ_j is the traffic intensity of node j obtained by:

$$\rho_j = \sum_{u=1}^{I} \frac{\alpha_{ju}}{\mu_{ju}}. \tag{6}$$

The arrival rates, α_{ju}, should be obtained by solving linear traffic equations as follows [16]:

$$\alpha_{ju} = \lambda_{ju} + \sum_{k=1}^{N} \sum_{v=1}^{I} \alpha_{kv} r_{kv,ju};\ j = 1, \ldots, N,\ u = 1, \ldots, I \tag{7}$$

where λ_{ju} is the exogenous arrival rate of class-u customers at node j. Also, we assume that the above traffic equations have a solution such that the traffic intensities are smaller than one due to stability. In the above formulation, we assume that there is not any buffering for the customers at each serving node, i.e., infinite-server nodes without any limitation in their service rates.

For the cases where we assume a fixed number of customers at the whole network, i.e., a closed queueing network ([15], [16]), the above properties are preserved by the following changes in the related equations:

$$\lambda_{ju} = 0,\ r_{ju,0} = 0;\ j = 1, 2, \ldots, N,\ u = 1, 2, \ldots, I. \tag{8}$$

In a closed queueing network, there is not any interaction between the network and exogenous world and all the routings are among the nodes. Also, in the set of traffic equations corresponding to closed queueing network we do not need the stability condition $\rho_j < 1$.

For the proposed model, we can consider two different average dwell times for new and handoff users in a cellular network, by considering two different classes of mobiles. In the next section, we apply this mobility model to obtain an analytical solution for spatial traffic distribution in a typical region.

III. Analytical Computation of Spatial Traffic Distribution

Although, mobility is a process independent of the users' activities in connection to the communication services, spatial traffic distribution on the other hand is meaningful for active users only. In other words, the proposed mobility model is useful for users' location density in general, however, for some issues such as spatial distribution of the traffic load we need to focus on the mobility of active users, i.e., users in connected-mode. In this section, we obtain a closed form solution for spatial traffic distribution of active users. As we stated in the previous sections, we focus on a typical region with fixed number of active users, M, i.e., conditional spatial traffic distribution. In this case, the proposed mobility model of the previous section is changed to a closed queueing network. Since, in this section, we consider only the mobility of active users in the network we should modify the proposed mobility model in order to consider new related issues.

In this section, we consider two independent departure rates for a typical class-u active user in a typical subregion, j. These include the departure rate due to mobility (μ_{ju}^d) and the departure rate (μ_{ju}^c) due to expiry of the service duration time, e.g., call duration time. For simplicity, we assume negative exponential distribution for inter-arrival times corresponding to both rates. So, the departure rate of the concerned user is the sum of both rates. Therefore, in each subregion, an active user, i.e., user in connected-mode, may transfer to idle-mode with an independent rate equal to inverse of its average service duration time. Also, the departure rate due to mobility at boundary subregions (Fig. 2) may result in similar effect due to migration of an active user to neighboring regions, i.e., handoff process. These rates, lead to $(M-1)$ active users in our typical region and in our analysis we exclude these cases. Furthermore, if the number of active users in the specific region increases due to arrival of a new call or migration of an active user from neighboring regions the status of that region, i.e., $(M+1)$, is excluded in our analysis. In general, these two types of events, i.e., increasing and decreasing the number of active users in a typical region, do not have an explicit relation with each other. In fact, with respect to time-varying attribute of the traffic load in the specific region, we focus on the time intervals that the number of active users in the concerned region is equal to M. The M active users are independent, hence, we focus on the spatial traffic distribution of one active user and extend the result to M active users. Therefore, we consider the following modification in the proposed mobility model.

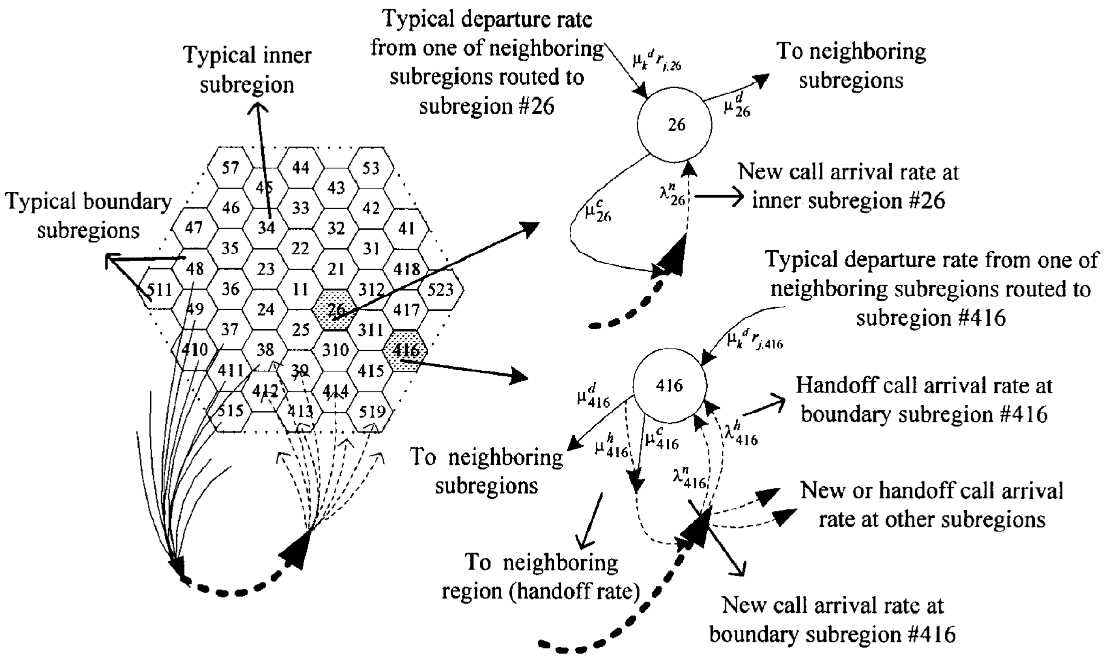

Fig. 2. Proposed mobility model with single class of active user including the processes that cause the number of active users deviates from M.

We assume that any event that leads to a decrease in the number of active users is immediately followed by another event that increases the number of active users. This is not a limiting modification because in our model the time interval between disappearance and appearance of a typical active user in the specific region does not affect its spatial traffic distribution. By this modification in the mobility model (Fig. 2), we are able to compute the stationary distribution of the spatial traffic.

One important issue in this modified model is how we relate the departures from the specific region to that of arrivals at all subregions. The departure processes that lead to decrease in the number of active users, are the rates due to expiry of service duration time and the handoff or migration rate from the boundary subregions to the outside of the specific region (Fig. 2). Similarly, arrivals are divided into two groups, new and handoff (migrating) calls. The latter arrive in boundary subregions, however, the new calls arrive in all subregions (Fig. 2), according to a spatial statistical pattern. Therefore, we require the ratio between new call arrival rate (λ^n) and handoff call arrival rate (λ^h) at the specific region. Also, we need the spatial statistical pattern for the new calls at all subregions and for handoff calls at all boundary subregions. This information in general, depends on the traffic status of the neighboring regions and the policies applied in the network. With respect to Fig. 2 and above discussions, we have the following relations:

$$\lambda_j^n = \frac{\lambda^n}{\lambda^n + \lambda^h} p_j^n r_{0,ju}^n;\ j \in S, u \in C, \tag{9}$$

$$\lambda_j^h = \frac{\lambda^h}{\lambda^n + \lambda^h} p_j^h r_{0,ju}^h;\ j \in S_B, u \in C, \tag{10}$$

where S is the set of all subregions, S_B is the set of all boundary subregions and C is the set of all classes of active users. $\lambda_j^n(\lambda_j^h)$ is the new (handoff) call arrival rate at subregion j. Also, p_j^n and p_j^h represent the spatial statistical patterns for new and handoff active users at subregion j that may include average blocking and dropping probabilities, respectively. And, $r_{0,ju}^n$ and $r_{0,ju}^h$ indicate the routing probabilities of a new or handoff arriving class-u active user at subregion j, respectively. We have the following relationships for these parameters:

$$\sum_{j\in S} p_j^n = 1; \quad \sum_{j \in S_B} p_j^h = 1; \tag{11}$$

$$\sum_{u \in C} r_{0,ju}^n = 1;\ \forall j \in S; \quad \sum_{u\in C} r_{0,ju}^h = 1;\ \forall j \in S_B. \tag{12}$$

Thus, using the results of the previous section and the above modification, the spatial traffic distribution may be obtained by (2) and the traffic equations with respect to the following:

$$\mu_{ju} = \mu_{ju}^c + \mu_{ju}^d;\ u \in C, j \in S \tag{13}$$

where μ^c is the departure rate due to expiry of service duration time and μ^d is the departure rate from a subregion due to mobility, i.e., inverse of the dwell time at that subregion. The migration rate from the boundary subregions to the outside of the specific region (μ^h) is a part of μ^d (Fig. 2). Due to our modified mobility model, μ^c and μ^h return as external arrival rates (new or handoff) to the specific region.

The typical traffic equation (such as (7)) for class-u active users in a typical inner subregion is obtained as follows:

$$\begin{aligned} \alpha_{ju} = & \sum_{i=1}^{N}\sum_{v=1}^{I} \alpha_{iv} \frac{\mu_{iv}^d}{\mu_{iv}^c + \mu_{iv}^d} r_{iv,ju} \\ & + \sum_{i=1}^{N}\sum_{v=1}^{I} \alpha_{iv} \frac{\mu_{iv}^c}{\mu_{iv}^c + \mu_{iv}^d} \frac{\lambda^n}{\lambda^n + \lambda^h} p_j^n r_{0,ju}^n \\ & + \sum_{i \in L_4 \cup L_5} \sum_{v=1}^{I} \alpha_{iv} \frac{\mu_{iv}^d}{\mu_{iv}^c + \mu_{iv}^d} r_{iv,0} \\ & \cdot \frac{\lambda^n}{\lambda^n + \lambda^h} p_j^n r_{0,ju}^n; j \in S - S_B, u \in C \end{aligned} \tag{14}$$

where α_{ju} indicates the class-u input arrival rate at subregion j when we consider the effect of other subregions with respect to our modified mobility model. And $r_{iv,ju}$ represents routing probability for the departure of a class-v active user from subregion i to subregion j as a class-u active user, due to mobility. Obviously, this probability is zero when two respective subregions are not neighboring subregions. The second double summation indicates the departure of a class$-v$ active user from subregion i due to expiry of its service duration time that appears as a new class-u arrival at subregion j (with respect to modifications applied on the mobility model). Also, $r_{iv,0}$ indicates the routing probability for the class$-v$ departure from boundary subregion, i, to the outside of the specific region, due to mobility. Thus, the third double summation in (14) indicates the departure of a class-v active user from boundary subregion i that appears as a new class-u arrival at subregion j.

The traffic equation for class-u active users in a typical boundary subregion is obtained as follows:

$$\begin{aligned}\alpha_{ju} =& \sum_{i=1}^{N}\sum_{v=1}^{I}\alpha_{iv}\frac{\mu_{iv}^{d}}{\mu_{iv}^{c}+\mu_{iv}^{d}}r_{iv,ju}\\ &+\left(\sum_{i=1}^{N}\sum_{v=1}^{I}\alpha_{iv}\frac{\mu_{iv}^{c}}{\mu_{iv}^{c}+\mu_{iv}^{d}}\right.\\ &\quad\left.+\sum_{i\in L_4\cup L_5}\sum_{v=1}^{I}\alpha_{iv}\frac{\mu_{iv}^{d}}{\mu_{iv}^{c}+\mu_{iv}^{d}}r_{iv,0}\right)\\ &\cdot\left(\frac{\lambda^n}{\lambda^n+\lambda^h}p_j^n r_{0,ju}^n+\frac{\lambda^h}{\lambda^n+\lambda^h}p_j^h r_{0,ju}^h\right); j\in S_B, u\in C.\end{aligned} \tag{15}$$

In (15), when compared to (14), we have handoff (migration) arrival rates in addition to new call arrival rates in the second and third summations. In fact, the second and third summations in both eqns. ((14), (15)), are due to modifications that we apply on the proposed mobility model in order to consider the mobility of active users only. As we observe in a closed queueing network, the set of traffic equations are represented by (14) and (15) for different values of j and u. Obviously, traffic equation for one of the customer classes at one node, will depend on other traffic equations and should be removed. In other words, we can consider a closed queueing network as an open queueing network such that one of the nodes plays the role of the exogenous world. We consider two cases in this respect. At first, we consider network with single class of customers, secondly, the network with multiple classes of customers. In the first case, we assume that one of the nodes, for example, the last node, N, plays the role of exogenous world. In this case, the departure rate from this node is equivalent to exogenous arrival rate at the other nodes. Therefore, we should omit the last traffic equation corresponding to α_N and replace α_N by $\mu_N^c+\mu_N^d$ in the other traffic equations. In fact, we assume the traffic intensity of the last node is equal to one, otherwise, we will have a scaling factor for all α_j's and in (3) it will be absorbed in the normalization constant. So, it does not affect the probability distribution. In the last node, N, the number of customers is equal to $(M-\sum_{j=1}^{N-1}n_j)$, because we have a closed queueing network with fixed number of customers, M. Thus, when the total number of customers in the other nodes equals M, the departure rate from the last node will diminish.

With respect to the above discussions and Jackson's theorem, we will have the stationary distribution for the modified mobility model as follows:

$$\begin{aligned}\pi(\mathbf{n}) =& b_n\prod_{i=1}^{N-1}\frac{\alpha_i^{n_i}}{n_i!\left(\mu_i^c+\mu_i^d\right)^{n_i}}\frac{1}{\left(M-\sum\limits_{j=1}^{N-1}n_j\right)!};\\ \mathbf{n} =& (n_1,n_2,\ldots,n_{N-1});\ \|\mathbf{n}\|=\sum_{j=1}^{N-1}n_j\le M\end{aligned} \tag{16}$$

where b_n is the normalization constant in order to have a stationary probability distribution. Eqn (16) indicates the probability of n_1 active users to be present at subregion 11, n_2 active users to be present at subregion 22, etc., in the specific region (Fig. 2).

For the second case, the closed queueing network with multiple classes of customers, we find the stationary distribution in detail, i.e., with respect to different classes of customers. To this end and with respect to the previous case, we consider the last class of the customers at the last node as exogenous world and thus, omit the traffic equation corresponding to α_{NI}. In this case, we replace α_{NI} by $\mu_{NI}^c+\mu_{NI}^d$ similar to the first case. Thus, we will have the following stationary distribution with respect to Jackson's theorem:

$$\begin{aligned}\pi(\mathbf{n}) =& b_n\prod_{i=1}^{N-1}\prod_{u=1}^{I}\frac{\alpha_{iu}^{n_{iu}}}{n_{iu}!\left(\mu_{iu}^c+\mu_{iu}^d\right)^{n_{iu}}}\\ &\prod_{u=1}^{I-1}\frac{\alpha_{Nu}^{n_{Nu}}}{n_{Nu}!\left(\mu_{Nu}^c+\mu_{Nu}^d\right)^{n_{Nu}}}\\ &\cdot\frac{1}{\left(M-\sum\limits_{j=1}^{N-1}\sum\limits_{u=1}^{I}n_{ju}-\sum\limits_{u=1}^{I-1}n_{Nu}\right)!};\\ \mathbf{n} =& (\mathbf{n}_1,\mathbf{n}_2,\ldots,\mathbf{n}_N);\ \|\mathbf{n}\|=\sum_{j=1}^{N-1}\sum_{u=1}^{I}n_{ju}+\sum_{u=1}^{I-1}n_{Nu}\le M.\end{aligned} \tag{17}$$

Eqn (17) indicates the probability of $n_{11},n_{12},\ldots,n_{1I}$ corresponding to class-1, class-2, ... and class-I active users that are present at subregion 11 and $n_{21},n_{22},\ldots,n_{2I}$ corresponding to class-1, class-2, ... and class-I active users that are present at subregion 22, etc. Also, we are able to obtain the probability of n_j customers of all classes existing at node j by applying suitable summations over (17). Eqns (16) and (17) may be obtained by considering only one active user (M equals 1) and extending the result to M active users with respect to their independence.

Actually, we obtain a fine spatial staircase approximation for the spatial traffic distribution in the specific region with a fixed number of active users, M. The spatial resolution of this distribution depends on the size of the subregions.

In the next section, we describe how the departure rates corresponding to each node can be determined with respect to some general distributions previously suggested for the related statistical parameters.

IV. Generality and Flexibility of the Proposed Mobility Model

In this section, we justify the flexibility and generality of the proposed mobility model. In this respect, we consider general distributions for the mobility-related statistical parameters in a cellular network. These parameters include cell dwell time, i.e., the duration time that a typical user resides in a cell and channel holding time, i.e., the duration time that a typical active user occupies a channel in a cell. Also, the concerned general distributions include sum-of-hyper-exponentials (SOHYP), hyper-Erlang and Cox. Another issue considered in this section regards to flexibility of the proposed mobility model for use in simulations.

A. Modeling Cell Dwell Time

Cell dwell time is a statistical parameter that only depends on the mobility of the users. There exist several distributions for modeling cell dwell time in the literature ([10]–[13]). Two most general forms in this respect are sum-of-hyper-exponentials (SOHYP) and hyper-Erlang distributions. At first, we focus on SOHYP distribution.

A random variable with SOHYP distribution consists of several concatenated phases such that each phase consists of several stages. Each stage is a negative exponential distributed (NED) random variable and each phase is a hyper-exponential random variable, i.e., at each phase one stage is selected with a certain probability. The probability distribution of SOHYP is the convolution of hyper-exponential distributions as in the following [11]:

$$f_{T_D}(t) = f_{T_D(1)}(t)^* f_{T_D(2)}(t)^* \cdots ^* f_{T_D(N)}(t) \tag{18}$$

where * denotes convolutional operation and

$$f_{T_D(i)}(t) = \sum_{k=1}^{M(i)} \alpha(k,i)\mu_D(k,i)\exp(-\mu_D(k,i)t);$$
$$\sum_{k=1}^{M(i)} \alpha(k,i) = 1, \alpha(k,i) > 0,\ i = 1,\ldots,N. \tag{19}$$

In the above equation, N is the number of phases and $M(i)$ is the number of stages in phase i. The schematic of SOHYP has been sketched in Fig. 3. In general, we may have similar stages in this configuration. It is shown that SOHYP distribution has the capability of representing a random variable with coefficient of variation smaller, equal, or greater than one ([11], [12]).

For a typical subregion in the proposed mobility model, we consider several mobility classes for users, such that each class has its distinct NED dwell time. This corresponds to service time for a class of customer in the equivalent queueing network. Thus, we can apply an analogy between our proposed mobility model and SOHYP distribution. To this end, we assume that each subregion represents a phase of SOHYP. And mobility classes at a subregion correspond to different stages in corresponding phase. On the other hand, a user departs the specific cell after expiry of its dwell time in different directions with its corresponding probabilities. We include these different

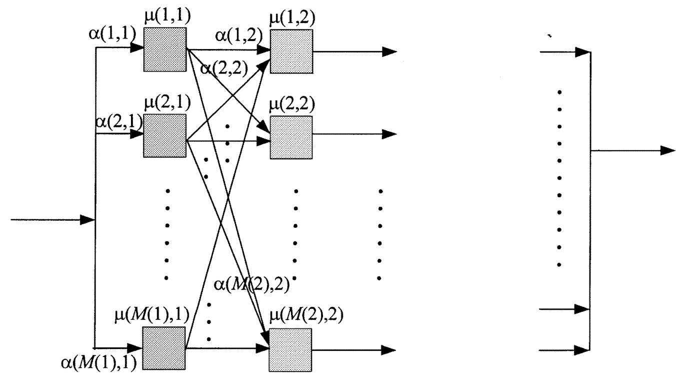

Fig. 3. Schematic representation of SOHYP (each square indicates an NED random variable).

departure directions as different mobility classes of the users. We should consider routings such that the number of traversed subregions is equivalent to the required number of phases in SOHYP distribution. Therefore, in this approach, $\alpha(k,i)$'s in (19) appear in routings and class conversion probabilities and $\mu(k,i)$'s appear in departure rates from the corresponding subregion and are dependent upon user's mobility classes. Then, we are able to map SOHYP distribution by proper parameters setting in the proposed mobility model.

Another general distribution proposed for modeling cell dwell time is hyper-Erlang distribution [13]. The probability density function of such a random variable is as follows:

$$f_{T_D}(t) = \sum_{i=1}^{N} \alpha(i) \frac{(m_i\mu_D(i))^{m_i}\, t^{m_i-1}}{(m_i-1)!} \exp(-m_i\mu_D(i)t);$$
$$\sum_{i=1}^{N} \alpha(i) = 1; \quad \alpha(i) \geq 0. \tag{20}$$

In the above equation, N is the number of Erlangs, m_i is the number of NED random variables at i-th Erlang and $\mu_D(i)$ is the decay rate of each NED random variable at i-th Erlang. The schematic of hyper-Erlang distribution is sketched in Fig. 4. In this configuration, with a certain probability the concerned random variable selects one Erlang distribution. Each Erlang distribution has its independent shape parameter, i.e., the number of similar concatenated NED random variables. It is shown that this distribution is capable of modeling any arbitrary distribution with rational characteristic function, equivalent to rational form for the Laplace transform of its probability density function [13]. The key point in this respect is due to the property that with increasing the shape parameter, probability density function of Erlang distribution approaches to the delta function. With respect to sampling theorem, the generality of hyper-Erlang distribution can be inferred intuitively.

In order to map hyper-Erlang distribution on the proposed mobility model, we consider different Erlangs (Fig. 4) corresponding to different mobility classes. We consider dwell time at each subregion as an NED random variable depending on the mobility class of the user. Although, we can assume Erlang distribution for dwell time at each subregion, but in former method we have a configuration similar to that in representing SOHYP. We should determine routings such that the number of traversed

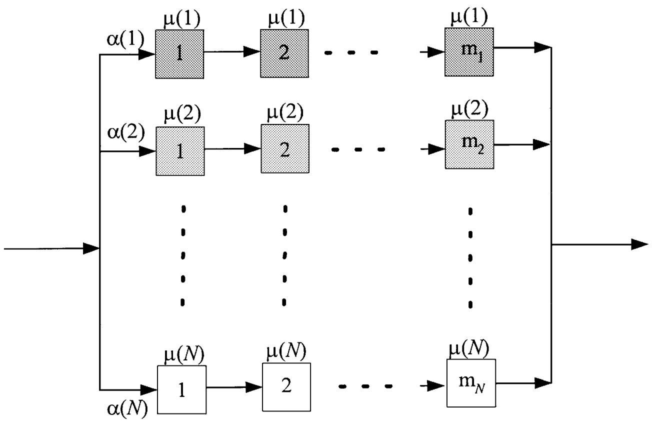

Fig. 4. Schematic representation of hyper-Erlang (each square indicates an NED random variable).

subregions (equivalently the number of similar NED's) corresponding to a mobility class represents the shape parameter of the corresponding Erlang. Also, similar to discussions regarding SOHYP, we can include different directions for cell departure in different mobility classes.

With respect to above discussions, we are able to map both SOHYP and Hyper-Erlang distributions on the proposed mobility model such that the dwell time at each subregion is an NED random variable.

It is worth mentioning that if the number of NED random variables in above general distributions is smaller than the least number of subregions possibly traversed, we can consider the dwell time of extra subregions as NED random variables with very high decay rate (approaching delta function). So, in this case we will have a good approximation for the concerned general distribution.

Also, above approaches, enable us to consider location-dependent cell dwell time for new and handoff users, distinctly.

B. Modeling Channel Holding Time

Although, cell dwell time is related to the mobility pattern and is independent of the communication services, channel holding time is a statistical parameter that is affected by both mobility pattern of the active users and duration time of their services. We may consider channel holding time in two approaches.

The first approach is by considering cell dwell time and service duration time independently, using general distributions such as SOHYP or hyper-Erlang. Obviously, by our discussion in the previous section the proposed mobility model can represent the above two general distributions. But, we should note that the service time is a process independent of the mobility process of active users. Since at each subregion we require the rate of departure for active users, we should include both processes at this departure rate.

The second approach is to consider channel holding time directly. As we stated, channel holding time is a time variable mediating between two independent time variables, i.e., cell dwell time and service duration time. But in this new approach, we model channel holding time without considering the two subordinated processes. In fact, in this case, it is assumed that we

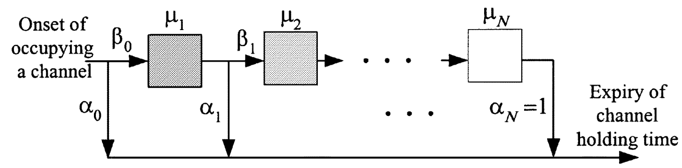

Fig. 5. Schematic representation of Cox model (each square indicates an NED random variable).

obtain a specific distribution for channel holding time by field data gathering and their statistical processing. We consider Cox model as a suitable general model for channel holding time. In fact, hyper-exponential and hyper-Erlang distributions are special cases of Cox model. Also, this model has attributes similar to hyper-Erlang distributions and can be employed to model any arbitrary distribution with rational characteristic function [15]. The schematic of this model is sketched in Fig. 5. The first branch (indicated by α_0) can be removed because that is useful for modeling delta in the probability density function. But, zero channel holding time is not justified [11]. Thus, we consider Cox model without the first branch ($\alpha_0 = 0$). Then, the probability density function of a Cox random variable is as follows [15]:

$$f_T(t) = \sum_{m=1}^{N} \beta_0\beta_1\cdots\beta_{m-1}\alpha_m e^{-\mu_1 t} * e^{-\mu_2 t} \cdots * e^{-\mu_m t};$$
$$\alpha_i + \beta_i = 1;\ i = 0, 1, \ldots, N. \tag{21}$$

Now consider that the dwell time at a typical subregion for a typical active user follows an NED distribution. While departing from that subregion the concerned user routes to another neighboring subregion with a certain probability, or it completes its service and leaves the network with another probability. With this methodology, we have a Cox model. Depending upon the number of phases in Cox model (NED random variables in Fig. 5) we should consider specific routings to traverse sufficient number of subregions. Regarding our discussions on SOHYP, we can consider different directions for cell departure at the start of user's activity in the specific region. These directions can be considered as different initial classes of active users. For a definite channel holding time distribution, we should specify the branching probabilities as well as the parameter of each negative exponential server that simply are mapped to proposed mobility model with respect to above discussions. To this end, α_i's and β_i's correspond to the routings to the outside of the cell, i.e., releasing the occupied channel, and routing to neighboring subregions, respectively. And the decay rate of each NED in Fig. 5 is mapped on the departure rate for the active user at the corresponding subregion. Also, in this configuration we can represent location-dependent channel holding time for new and handoff active users distinctly.

It is worth mentioning that the above mappings in Section IV-B and Section IV-C are not unique and simple. However, we have only intended to show the feasibility of the concerned mappings. Also, the key point in above flexibilities refers to the capability of considering several classes of customers in the equivalent queueing network. However, this capability increases the complexity of the related traffic equations linearly.

C. A Suitable Framework for Simulations

Until now, we have focused on the statistical parameters of the users such as cell dwell time and channel holding time. In this subsection, we will observe the generality and flexibility of the model with regards to its capability in considering physical parameters of the mobility process. In other words, in previous two subsections, we assume that we obtain specific distribution for the concerned statistical parameters by related field data gathering and statistical processing. As we observed in previous subsections, there is not a unique approach for mapping the statistical distributions for mobility-related parameters on the proposed mobility model. On the other hand, each approach leads to a set of model parameters and then a specific spatial traffic distribution. In fact, mobility-related statistical parameters cannot uniquely determine the spatial traffic distribution and we require some information about physical parameters of the mobility such as velocity and moving direction and especially routings in the proposed mobility model.

In this respect, the proposed mobility model provides an approach by which it can be employed for simulations. This issue is more or less obvious, because the proposed mobility model does not have any specific restriction with respect to the number of subregions or their shapes and sizes. We may simply consider subregions such that they cover the typical geographical region. Thus, it is sufficient to determine the routing probabilities and the method of changing velocity or directions. Also, we may consider the points of these changes to be at the boundary crossings of the subregions, for example, we may consider the subregions as the parts of the city streets between two crossroads.

On the other hand, with respect to the capability of the model to include the statistical distribution at the granular level, we can employ some simple dwell time distributions such as the one considered in [10]. Such a distribution assumes uniform location density as well as a constant velocity and fixed direction after initial probabilistic settings. Such assumptions are not justified at the level of a cell, but at the level of a granular subregion, they can be justified. Applying dwell time distribution obtained in [10] is useful both in simulations and in finding the distribution of the statistical parameters at the level of the cell after some rigorous computations.

It is important to note that the proposed mobility model can lead to a closed form for spatial traffic distribution at the level of a cell. Also, this model has flexibilities in considering statistical and physical parameters with respect to above discussions.

V. Numerical Examples

In this section, we consider three simple examples in order to apply the proposed mobility model and compute active user's location density.

Example I: We assume the following assumptions for a typical region in this case:

a) One class of active users.

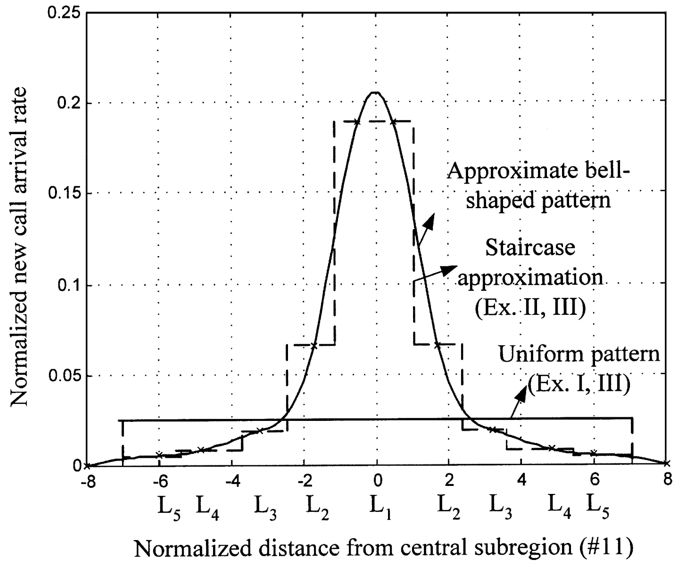

Fig. 6. Two different statistical spatial patterns for new call arrival rate.

b) Similar dwell time for each user at each subregion with average $(1/\mu^d)$ of 1 minute.

c) Similar service duration time for each active user at each subregion with average $(1/\mu^c)$ of 2 minutes.

d) Uniform spatial statistical pattern for arrival rate of new active users as in Fig. 6

e) Probability of migration from outside of the specific region to be proportional to the length of boundary edges at boundary subregions as in the following:

$$\begin{aligned} p_j^h &= \frac{1}{N_b}; \\ j \in L_{4-1} &= \{42,43,45,46,48,49,411,412,414,415,417,418\}, \\ p_j^h &= \frac{3}{N_b}; \quad j \in L_{4-2} = \{41,44,47,410,413,416\}, \\ p_j^h &= \frac{4}{N_b}; \quad j \in L_5 \end{aligned} \tag{22}$$

where N_b is the number of boundary edges, equal to 54 (Fig. 1).

f) Three cases of λ^n/λ^h,i.e., 0.5, 1, 2.

g) Symmetric routing probabilities for departure of a typical user in one subregion, due to mobility, to neighboring subregions.

Example II: We assume all of the assumptions of Example I, except the assumption (d). We replace the following assumption in this respect:

d) Approximated bell-shaped spatial statistical pattern for arrival rate of new active users, as in Fig. 6. We consider symmetric pattern such that arrival rate at all subregions belonging to one layer have the same rate.

Example III: In this example, we consider a more complex region such as an airport. We consider two classes of active users, pedestrian user (p) and vehicular user (v). We assume the class conversion such that by approaching to the central subregion (#11 in Fig. 2) from boundary subregions, we have more probability for class-v to class-p conversions and vice versa.

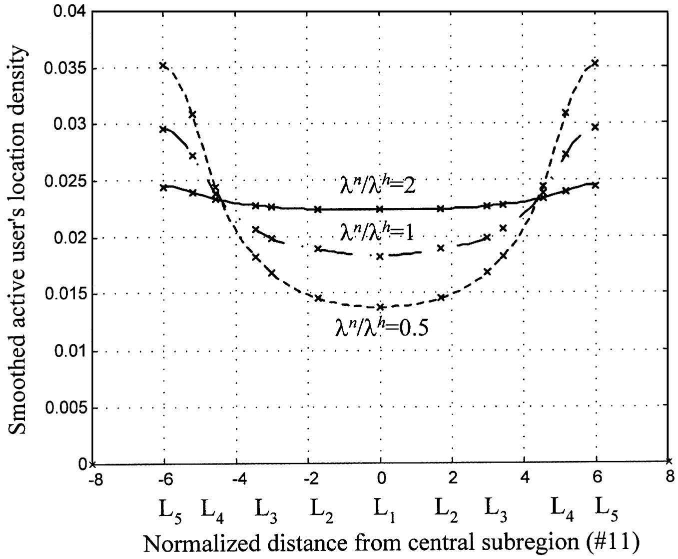

Fig. 7. Location density for uniform arrival pattern (Ex. I).

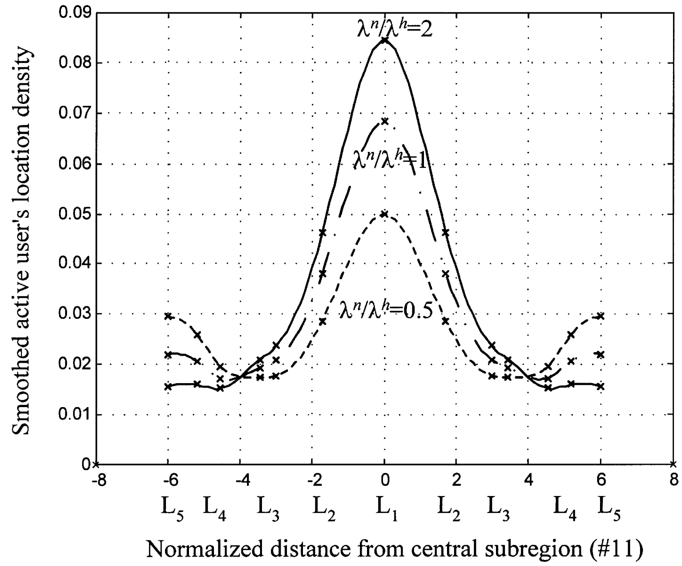

Fig. 8. Location density for approximate bell-shaped arrival pattern (Ex. II).

However, we do not assume any class conversion for traversing the subregions at the same layer, for pedestrian users in the direction toward central subregion, and for vehicular users in the direction out of central subregion. Briefly, we have the following assumptions in this example:

a) Two classes of active users, p, v.
b) Similar dwell time at each subregion with average $(1/\mu_v^d)$ of 1 minute for class-v and average $(1/\mu_p^d)$ of 10 minutes for class-p.
c) Similar service duration time at each subregion with average $(1/\mu^c)$ of 2 minutes for both classes.
d) Uniform and approximated bell-shaped spatial statistical pattern for arrival rate of new active users, as in Fig. 6. We consider symmetric pattern such that arrival rate at all subregions belonging to the same layer have the same rate.
e) As in Example I.
f) Assume that λ^n/λ^h equals 4.
g) As in Example I.
h) Assume following relations for class conversion and routings:

$$r_{ip,jp} = \begin{cases} \frac{1}{12}; & L(i) = L(j) \\ \frac{1}{6}; & L(i) > L(j) \\ \frac{1}{6}\frac{1}{1+2^{L(i)-1}}; & L(i) < L(j) \end{cases};$$

$$r_{iv,jv} = \begin{cases} \frac{1}{12}; & L(i) = L(j) \\ \frac{1}{6}; & L(i) < L(j) \\ \frac{1}{6}\frac{1}{1+2^{5-L(j)}} & ; L(i) > L(j) \end{cases};$$

$$r_{ip,jv} = \begin{cases} \frac{1}{12}; & L(i) = L(j) \\ 0; & L(i) > L(j) \\ \frac{1}{6}\frac{2^{L(i)-1}}{1+2^{L(i)-1}}; & L(i) < L(j) \end{cases};$$

$$r_{iv,jp} = \begin{cases} \frac{1}{12}; & L(i) = L(j) \\ 0; & L(i) < L(j) \\ \frac{1}{6}\frac{2^{5-L(j)}}{1+2^{5-L(j)}}; & L(i) > L(j) \end{cases};$$

$$r_{0,jp}^n = 2^{5-L(j)} r_{0,jv}^n (j \in S);\ r_{0,jv}^h = 2r_{0,jp}^h (j \in S_B)$$

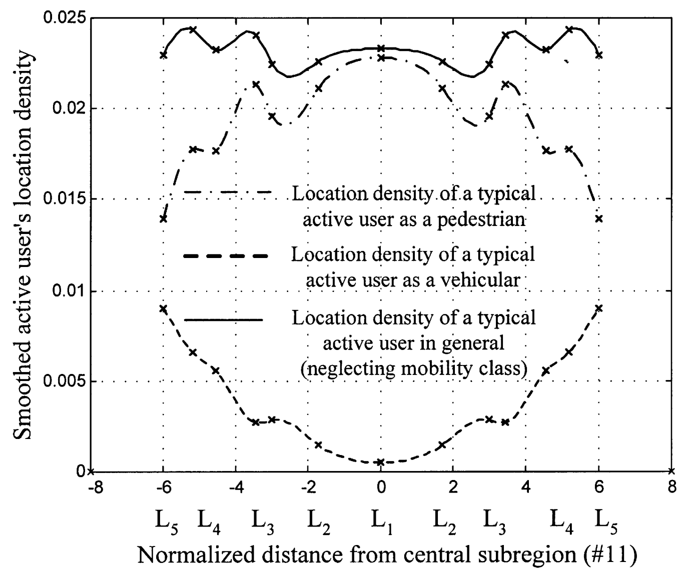

Fig. 9. Location density for uniform arrival pattern (Ex. III).

where $L(i)$ indicates the layer in which subregion i belongs to it. Also, in the above relations we assume that subregions i, j are neighboring regions.

One of the statistics that is a special case of spatial traffic distribution is the active user's location density that indicates the probability of a typical active user existing in each subregion. This statistic can be obtained by our spatial traffic distribution when M equals one. The resultant traffic densities for above three examples can be observed in Figs. 7–10. In Examples I and II, we observe the effect of statistical arrival pattern of new active users on the location density, however, in example III we observe the effect of routings on the location density as well. As we observe in Figs. 7–10, we have different location densities for two groups of subregions at each of layers L_3 and L_4, with respect to various situations and their neighbors in the specific region (see (22) and Fig. 2).

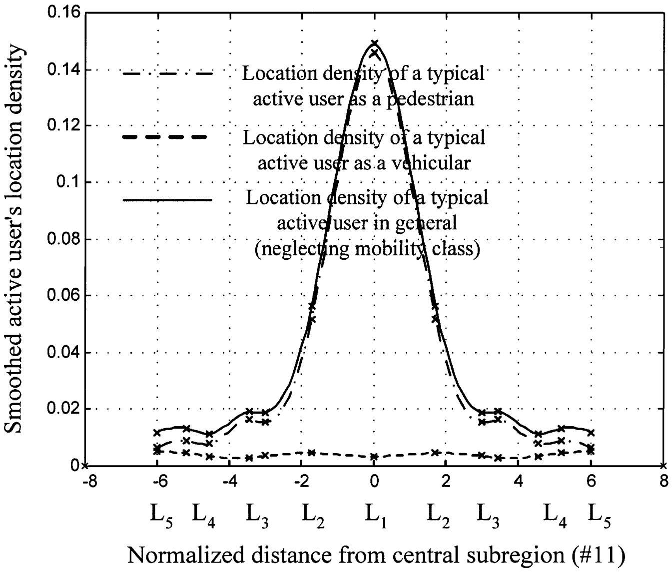

Fig. 10. Location density for approximate bell-shaped arrival pattern (Ex. III).

VI. Conclusions

In this paper, we focused on the mobility and spatial traffic distribution in wireless multimedia networks and especially in multimedia cellular networks. We proposed a general mobility model based on region splitting such that the interconnections between subregions and their corresponding dwell time parameters specify the model parameters. Then, we made an analogy between this model and a multi-class Jackson queueing network with infinite-server nodes. The most important property of such a network is that its stationary distribution has a product-form solution.

Following that, we modified the proposed mobility model in order to compute spatial traffic distribution of the active users, i.e., users in connected-mode, in a typical region. In this respect, we considered the statistical spatial arrival pattern for new and handoff active users. Then, we justified the flexibility and generality of the proposed mobility model due to its capability in representing some general distributions such as SOHYP, hyper-Erlang and Cox which had been previously proposed for mobility-related statistical parameters, e.g., cell dwell time and channel holding time. Also, we discussed briefly the capability of the proposed mobility model to be employed in simulations. In order to show the application of the proposed model we computed the active user's location density for three mobility scenarios.

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