SMM: Mathematical Framework of a Scalable Mobility Model

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ABSTRACT
In this paper, we present a novel mathematical framework of a mobility model that can be applied to a large number of possible horizontal environments, ranging from local area networks (LANs) to wide area networks (WANs) for the prediction and tracking of mobile users. This new mobility model termed 'Scalable Mobility Model' (SMM) provides a realistic set of paths for both individual and aggregate subscriber movement by assigning mobile users into specific classes of mobility based on their mobility characteristics, attraction points, geographical environments and time periods. The core technique used to implement these important mobility features in SMM is the introduction of a new concept referred to as the Pole of Gravity. Our mobility model has been decomposed into three processes termed as the physical, gravity and fluid sub-models. Using this new concept, we show how SMM can effectively characterize user mobility for the City Area Model of Avon district and the City Centre of Bristol, UK, having an extension of 40 km by 40 km and 8 km by 8 km respectively. We also present simulation results to illustrate the effect of accurate mobility by comparing our realistic mobility model, SMM, with the well know Random Waypoint model. Specifically, we show how the choice of a mobility model affects channel utilization and handover performance issues for the mobile environment.

Categories and Subject Descriptors
C.2 [**Computer-communication networks**]: *Wireless communication*; C.4 [**Performance of Systems**]: Modeling techniques

General Terms
Performance, Design, Theory

Keywords
Mobility models, mobile networks, cellular planning and deployment, mobility management, radio resource management

1. INTRODUCTION
Much research effort has been spent in the analysis of mobility patterns to characterize subscriber movement behavior. In this context, different mobility models describing either individual user behavior or aggregate movement flow with varying degrees of implementation complexity have been proposed to investigate the issues related to location management [8], radio resource allocation [9] and handoff management [13]. The need for different mobility models arises from the fact that these models suffer from limitations. They can only approximate certain practical scenarios and fail to work effectively when applied to different cellular network configurations because they are not able to provide accurate and reliable results. Bearing this in mind, we have designed a novel algorithmic mobility model which can be scaled to any demographic topology while retaining its ability to describe the conscious traveling path of subscribers on a daily basis.

The remainder of the paper is organized as follows. Section 2 highlights the main types of mobility models used in literature to describe user movement. In Section 3, we discuss the motivation behind our work and introduce the Pole of Gravity concept. Section 4, highlights our system model and gives a detailed description of the physical, gravity and fluid sub-models. Section 5 gives an in-depth discussion of the mathematical framework for the gravity and fluid laws. Section 6 shows the application and scalability of the SMM and its ability to describe user movement behavior for an urban scenario. Section 7 illustrates the performance comparison of SMM against Random Waypoint model while investigating channel utilization and handover performance issues and finally Section 8 concludes the paper and outlines the scope for future work.

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2. PROBING THE LITERATURE
Mobility models are important tools which have been used to describe human movement in the simulation and analysis of system performance and optimization of mobile networks.

Most of the work in the literature related to the mobile environment has modeled individual subscriber behavior using simple models based on Brownian motion [2], the random walk [7] or Markovian models [4]. These models characterize individual user behavior by relying on idealized assumptions, such as uniform user distribution, randomly chosen fixed movement defined through transitional probability states, which are known *a priori* and speed of the subscriber uniformly selected from a given speed range.

Aggregate population movement has been well characterized using the fluid [3] and gravity models [5]. The fluid model characterizes aggregate population movement as flow of a fluid which is uniformly distributed over $[0, 2\pi]$ and assumes a uniform distribution of users moving with a mean associated velocity. Gravity models have been used extensively to characterize the concept of origin and destination trip and rely on the assumption that all trips start from a given area are attracted to other areas in direct proportion to the size of the attraction and in inverse proportion to the spatial separation between the points of travel. Gravity models have been used extensively in transportation research for the analysis and design of transportation systems and have been adapted to characterize user mobility in mobile systems.

To enhance the above existing mobility models, it is valuable to combine mobility modeling and transportation theory [5], to estimate the performance of a mobile network for a predefined service area. However, users with mobile terminals are less constrained to the transportation network hence such approaches are not applicable for short range building environments and ad hoc network types of scenarios [10].

Therefore, there is a requirement for a scalable algorithmic mobility model that can mimic the mobility of subscribers at an arbitrary range of granularity in dimensions of population (ranging from an individual, a football crowd to a wide area network), direction and distance, speed and time.

3. SMM: A NEW APPROACH FOR THE PREDICTION & TRACKING OF MOBILE USERS

3.1 Motivations

The main challenge in the implementation of SMM was to provide a scalable algorithm that can be applied to an arbitrary selected geographical area while retaining its ability to predict user movement behavior by capturing the key factors of mobility. Our framework relies on the following observations:

- The modeling approach of SMM is based on the exploitation of the recent results of open multiclass queuing networks theory [1] to the flow of subscribers at both microscopic and macroscopic level of granularity. These ave the ability to combine individual and aggregate movements respectively.
- Although individual user movment is autonomous, similar types of movement can be identified by mobile users the same profiles of specific mobility and call patterns. Therefore we have assigned mobile users into different classes of mobility based on the concept of attraction points, geographical environments and time factors.
- Existing mobility models do not have the ability to characterize user mobility at different granularities in space. In SMM, we use the Pole of Gravity (PG) concept to describe the spatial and temporal behavior of subscribers for a predefined service area.

3.2 Pole Gravity (PG)

A PG represents a geographical location that contains a mass of mobile users and constantly re-calculates the steady state value of each class of mobility with respect to the location's attraction which is time dependent. The PG is a stochastic model which conceptualizes the following aspects:

- Classes of Mobility – Individual mobile users same mobility characteristics and behaviors are grouped into a specific class of mobility. These features extend the movement of conscious traveling based on the direction selected by the subscriber during motion towards a specific destination. The corresponding class of mobility also characterizes the mobile users' calling behavior and use of services. For our model, three classes of mobility have been considered: *Business*, *Residential* and *Others*.
- Area Zones – The PG can be scaled to different granularities in space. The service areas under consideration have been categorized into different hierachical geographical areas ranging from City Area Model to environments. The City Area category, has been divided into four area types: *City Centre*, *Urban*, *Suburban* and *Rural*. Using the same model, user mobility can be defined at a more refined granularity in space. By focusing on only one type of area, user movement and its corresponding calling behavior can also be investigated for the City Centre. This specific area type can be further divided into four environments: *Working*, *Residential*, *Shopping* and *Streets*.
- Attraction Points (APs) – These represent locations that attract users with a specific class of mobility and at which individual users of that class may spend a considerable amount of time. The strength of attraction for each class of mobility at any PG varies during the day. Each class of mobility is assigned one of the following attraction weights, $w \in [0, 1]$, for example, dominant (0.9), normal (0.5), or null (0.1), based on the attraction of the environment at specific time of the day.
- Time Periods – The day is divided into periods during which certain types of movements and traffic patterns take place. The rush hour (RH) characterizes the movement of mobile users from/to the city centre where most business establishments are concentrated, or to/from the outskirts where most residential areas are located. Another time period refers to the busy hour (BH) where subscribers reside at certain APs (e.g. work places) for a considerable amount of time.

4. SYSTEM MODEL

SMM is based on the integration of three processes: *Physical*, *Gravity* and *Fluid* sub-models.

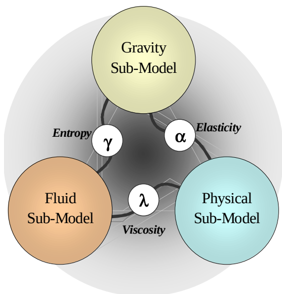

Figure 1. System Model

The interdependencies between the three sub-models are captured through the coefficients of elasticity (α), viscosity (λ) and entropy (γ) as illustrated in Figure 1.

4.1 Physical Sub-Model

The Physical Sub-Model defines the service area under consideration and divides it into different area zones which can be further divided into different environments. The main functions of the physical sub-model are detailed below.

4.1.1 PG characterization procedure

In order to mimic the real life scenarios of mobile users, we construct a geographical network which allows mobile users to roam from one location to another according to the constraints of the service area under consideration.

The physical sub-model first identifies the type of area zone under consideration and proceeds to the logical placement of the PGs by distributing them into one of the four environments on a real map. To provide a realistic distribution of subscribers over the service area, we use an initial subscriber distribution based on the demographic data of the terrain. This allows demographical information obtained from land surveys can be easily incorporated for the validation of the mobility model at a later stage. The initial population density of each class of mobility per square kilometer is embedded in each PG based on its logical placement.

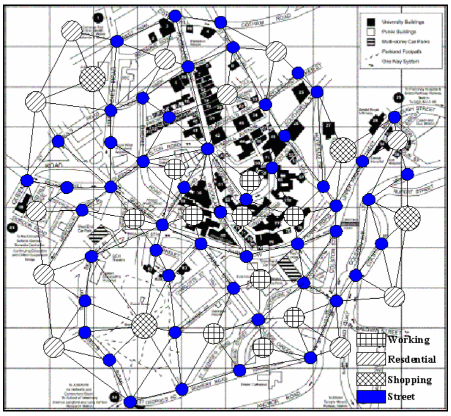

Figure 2. Overlay of PGs over City Area of Bristol, UK indicating different types of environments

An illustration of this process is shown for the City Centre of Bristol, UK, Figure 2, which covers an 8 km by 8 km. The cartographic data allows the characterization of the PGs as *Working*, *Residential*, *Shopping* and *Streets* environments indicated by the legend in Figure 2, while the demographic data specifies the population density of mobile users for each environment. At the start of the simulation, the density of mobile users in the Residential class of mobility has been assumed to be sparse in the *Working* environments as compared to the *Residential* environments. Thus population density of users differs throughout the coverage area creating "hot" and "cold" spots. The initial spatial distribution of the mobile users is given by Equation 1

$$z = re^{i\theta} \tag{1}$$

where $r = [\,0, \sqrt{S/\pi}\,]$, θ is uniformly distributed over $[0, 2\pi]$ and S is the surface area of the PG.

4.1.2 Angular connectivity

During movement, it is important for mobile users to respect the structures defined by the terrain. The physical sub-model identifies the road network and interconnects the PGs together through the "angular connectivity", R, which represents a measure of the arrangement of the edges of the multicalss queuing network interconnecting the PGs.

Each PG is divided into different sectors and the value of R varies from PG to PG based on how detailed the physical map is as shown in Figure 2. This process of logical connectivity among the PGs creates a virtual network which is overlaid on a real map and represents the most probable paths that mobile users will undertake once movement occurs.

4.2 Gravity Sub-Model

We have modified the gravity model to describe the spatial and temporal behavior of subscribers over the service area, by taking into account the concept of attraction at each PG and the population density per unit square extracted from the physical sub-model (Section 4.1.1). Our resulting gravity model in SMM has three main functions:

- Firstly, it assigns mobile users to their respective classes of mobility by taking into account the population density of users and the attraction weight of each class of mobility in the specific environment where the PGs are located.
- Secondly, it dictates the temporal behavior of mobile users for each class of mobility. This process is an enhancement of open multi-class queuing networks, more specifically a family of processor-sharing fluid models referred to as the head-of-the-line proportional processor sharing (HLPPS) fluid models [1].
- Finally, it ensures that the mobility model is kept under stable conditions by constantly re-calculating the steady state value of each class of mobility when a change in attraction occurs.

4.3 Fluid Sub-Model

Fluid models are continuous and conceptualize population movement as movement of mass rather than individual movement patterns [3] on a macroscopic level.

Our movement model exploits some features of fluid models but in addition has the ability to mimic mobile user displacement at both microscopic and macroscopic levels of granularity. The microscopic level is characterized by the Brownian motion model through a *transitional probability matrix*, while the macroscopic level is achieved by the aggregation of individual user movement to describe the movement of mass from one location to another. Once movement is initiated, subscribers move from PG to PG and their directions of movement follow the logical sets of paths defined by the angular connectivity. Therefore user movement is dictated in a predefined manner respecting the structures such as buildings blocks, rivers and streets.

Although the above feature allows user movement to respect the structures present in the service area, user movement in itself is autonomous and therefore can be random. In order to provide a realistic sets of paths undertaken by mobile users during motion, the important mobility concept of attraction together with the distance factor have been included in the fluid sub-model through the transitional probability matrix and governed by the '*fluid law*'.

4.4 Interaction between Sub-Models

This section addresses the interaction between the sub-models and show how they are interdependent on each other through the coefficients of *elasticity* (α), *entropy* (γ) and *viscosity* (λ).

In SMM, the spatial distribution of mobile users in the surrounding of the PGs over the service area is characterized by the physical sub-model and mobile user movement is initiated due to the changes in attraction experienced at the PGs governed by the gravity sub-model. This movement is influenced by the attraction and distance of surrounding PGs and is dictated by the fluid sub-model. To capture these properties in SMM, an integrated approach has been used which enables each sub-model to extract a structured set of input parameters required to tune the mobility model in order to be able to mimic user movement over a predefined service area.

The coefficient of viscosity affects motion by taking into account the relative distance among interconnected PGs and adds a weight to each set of paths from an originating PG to a destination PG. Variation of this parameter has the effect of controlling the distance covered by the movement of mass (flow of mobile users) and regulating its fluidity of movement through the geographical area under consideration. The corresponding analogy of movement of mass can be mapped to the flow of fluid such that the variation of the viscosity parameter causes the flow to either expand or compress. The rate at which this process takes place is determined by the coefficient of elasticity which fixes the rate at which the movement of mobile users from one PG to another. Variation of the coefficient of elasticity has the property of controlling the inflow and outflow of mobile users at a particular PG and therefore controls the speed of motion. The circulation of the flow of mobile users from one PG to another follows a process which can vary between a random and deterministic process, fixed through the coefficient of entropy. The latter estimates the attraction of each PG as compared to its neighboring interconnected PGs and adds a corresponding weight from the originating PG to the destination PG. Therefore the distance and attraction factors are dependent on the coefficients of viscosity and entropy respectively and are defined through the fluid law by an accompanying fluid equation.

Following the above discussion, we can formulate the fundamental meaning for the coefficient of elasticity, viscosity and entropy. The coefficient of elasticity is defined as the model's reactivity to control the inflow and outflow of mobile users when a change in attraction occurs among the PGs. Entropy is a measure of introducing a degree of friction between two different PGs while the coefficient of viscosity gives a perception of distance between the originating and destination PG.

5. MATHEMATICAL FRAMEWORK

This section describes the mathematical framework on which the gravity and fluid sub-models are based. The general notation used in the configuration of SMM is defined first followed by the concepts of the gravity and fluid laws.

5.1 General Notation & Definitions

The input parameters to our mobility model are detailed below:

T	Duration of simulation
M	Total number of mobile users in the area under consideration
N	Total number of Poles of Gravity
O	Total number of classes of mobility
R	Angular connectivity
α_j	Coefficient of elasticity at Pole of Gravity j (PG_j) and $0 \le \alpha_j \le 1$
λ_j	Coefficient of viscosity at Pole of Gravity j (PG_j) and $0 \le \lambda_j \le 1$
γ_j	Coefficient of entropy at Pole of Gravity j (PG_j) and $0 \le \gamma_j \le 1$
A_j	Mean Sojourn Time in PG_j
S_j	Surface area over which mobile users of any class of mobility are distributed over PG_j
$D_{j,K}$	Density of mobile users for class of mobility K, where K $\in$ (Business, Leisure, Shopping, Residential) for PG_j
$Att_{j,K}(t)$	Attraction function defining the weight for class of mobility K for PG_j at simulation time t and $0 \le Att_{j,K}(t) \le 1$
$C_{j,K}(t)$	Steady state value of number of mobiles in class of mobility K at PG_j
$l_{j,K}(t)$	Number of mobiles in class of mobility K for PG_j at simulation time t

5.2 Gravity Law

The 'Gravity Law' defines three important properties in SMM which are detailed in the following sub-sections.

5.2.1 Mobile User Characterization

To provide a realistic picture of mobile user distribution over the service area the gravity sub-model extracts the demographic data from the physical sub-model and together with the attraction weight of each class of mobility calculates the steady state value of mobile users, $C_{j,K}(t)$, for each class of mobility at time *t*.

This process is governed by the gravity law and is executed each time a change in the attraction weight occurs at a PG_j and is defined by Equation 2

$$C_{j,K}(t) = M \times P_{j,K}(t) \tag{2}$$

$P_{j,K}(t)$ is referred to as the *penetration matrix function* of users for each class of mobility at PG_j and is given by

$$P_{j,K}(t) = \frac{D_{j,K} \times Att_{j,K}(t) \times S_j}{\sum_{j=1}^{N} \sum_{K=1}^{O} D_{j,K} \times Att_{j,K}(t) \times S_j} \tag{3}$$

Equation 3 estimates the number of mobile users at specific locations and assigns them to their respective classes of mobility, taking account of their mobility characteristics. This generates a dynamic penetration matrix characterizing the mobile user penetration for each class of mobility at a specific PG. When a PG experiences a change in attraction, this matrix will change accordingly generating a different penetration matrix each time which in turn re-calculates the value of $C_{j,K}(t)$ in each class of mobility through Equation 2.

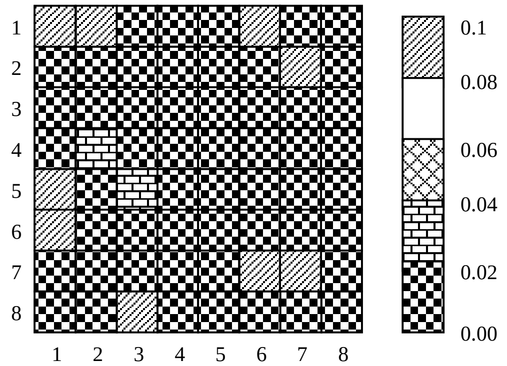

Figure 3. Penetration Matrix for City Centre of Bristol

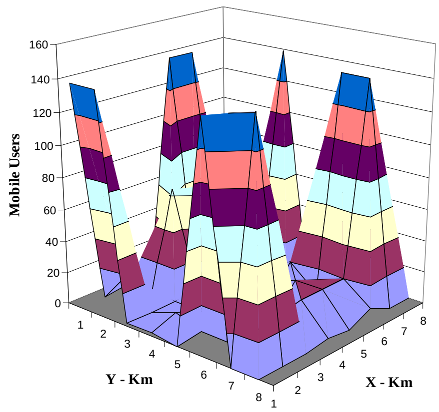

Figure 4. Mobile User Distribution over City Centre of Bristol, UK at 7.00 am

An illustration of this concept is shown in Figure 2 which depicts the overlay of PGs in Bristol City Centre, UK for 1700 mobile users at 7.00 am. Figure 3 illustrates the penetration matrix of the users over the area and the spatial distribution of subscribers over this service area is depicted in Figure 4. It can be clearly seen that the distribution of subscribers over the service area in Figure 4 is far from being uniform.

5.2.2 Temporal Behavior

The departure process of mobiles from one PG_j to another is determined by the inter-departure time, $ID_{j,K}(t)$. When a mobile enters a PG, it is assigned a residence time and when this time elapses, its new destination is chosen based on the attraction of surrounding PGs and distance factors governed by the fluid law.

This process is an enhancement of the HLPPS algorithm which states that the fraction of time spent serving a class present at a station is proportional to the quantity of the class there, and all the service goes into the 'first customer' of each class [1]. Therefore, the fraction of time spent by a mobile at a specific PG is proportional to the actual number of mobiles in its corresponding class of mobility. This process has the underlying property of the Markov process expressed by Equation 4

$$\mathrm{ID}_{j,K}(t) = A_j \alpha_j^{\varphi_{j,K}(t)} \tag{4}$$

where $\varphi_{j,K}(t)$ is defined as the population intensity given by the ratio of $l_{j,K}(t)$ and $C_{j,K}(t)$ is expressed below:

$$\varphi_{j,K}(t) = \frac{l_{j,K}(t)}{C_{j,K}(t)} \tag{5}$$

5.2.3 *Stability*

SMM extracts the key features of open multiclass queuing networks to characterize the spatial and temporal movement behavior of mobile users and follows a similar approach detailed in [1] to express the concept of stability.

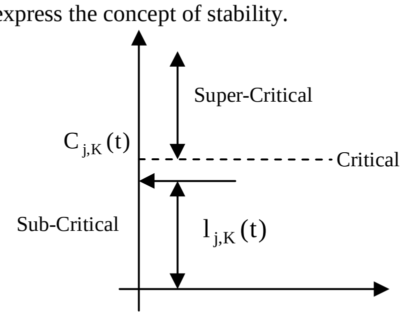

Figure 5. General Representation of Stability Conditions

With reference to Equation 5 and using the same analogy presented in [1], for each class of mobility, K, in a PG_j, three states can be identified: 1) $\varphi_{j,K}(t)<1$ referred to as sub-critical condition, 2) $\varphi_{j,K}(t)=1$ termed as the critical condition and 3) $\varphi_{j,K}(t)>1$ describes the super-critical state. These conditions are best illustrated in Figure 5. In SMM, each class of mobility is considered as a waiting queue implemented at the PG having infinite capacity and whose length varies dynamically to accommodate mobile users based on how attractive a specific class of mobility is at the PG. To ensure that the model is running under the stable conditions, condition 3 whereby $\varphi_{j,K}(t) > 1$ (i.e. $l_{j,K}(t) > C_{j,K}(t)$) is not desirable. This process is controlled by the gravity law which constantly re-calculates the steady state value of the number of mobiles in each queue, when a change in attraction occurs as detailed in Section 5.2.1.

5.3 Fluid Law

The fluid law defines user movement within the service area identified by the physical sub-model and this process is embedded in every PG. It is characterized by a transitional probability matrix which takes into account the factors of attraction strength among the PGs and distance in order to fix the circulation of mobile users in a deterministic way.

5.3.1 *Mobile User Movement*

When the inter-departure time of a specific class of mobility, K, in PG_i expires, calculated through the gravity law, user movement from PG, *i*, to the surrounding poles is initiated through the transitional probability matrix defined by Equation 6 which takes into account:

- The difference between the population intensity of class of mobility K of PG_j and PG_i which is expressed as $\Delta_{ji} = \varphi_{j,K}(t) - \varphi_{i,K}(t)$
- Distance of separation between, between PG_j and PG_i derived using the minimum distance criterion and given by $d_{\min ji}$

$$P_{i,KL}(t) = \gamma_i^{\tanh(\Delta_{ji}(t))} \times \lambda_i^{\tanh(d_{\min ji})} \tag{6}$$

One important property of the fluid law is that the limits of the transitional probability matrix, $P_{i,KL}(t)$, are strictly dependent on the coefficients of γ_i and λ_i thereby controlling the direction of movement as illustrated in Table 1.

During the simulation process, a class of mobility, K, in a corresponding PG_j will be attractive if the current number of mobiles in the queue of that class of mobility is less than that in the steady state; in other words, if the population intensity of that class, $\varphi_{j,K}(t)$, is less than 1. The probability of a mobile user leaving the source pole, PG_i, for a destination pole PG_j, is proportional to the excess population intensities of PG_i and PG_j which are derived from the gravity sub-model. This behavior is controlled by the coefficient of entropy, γ_i, as explained in Section 4.4. Furthermore, PG_i interconnects with its neighboring poles identifying the most probable paths that mobile users can take during movement. Using this information, the minimum distance between the originating PG_i and the destination PG_j is calculated and this value is weighted with respect to the coefficient of viscosity λ_i. This process is calculated for each PG and due to the transient behavior of attraction function the fluid law continually re-calculates the transitional probability matrix, which is determined in terms of steps at specific simulation intervals.

	$\Delta_{ji} \to -\infty$ (Repulsion)	$\Delta_{ji} = 0$ (Equilibrium)	$\Delta_{ji} \to \infty$ (Attraction)
$d_{\min ji} = 0$ (Near)	$\frac{1}{\gamma_i}$	1	γ_i
$d_{\min ji} \to \infty$ (Far)	$\frac{\lambda_i}{\gamma_i}$	λ_i	$\gamma_i \lambda_i$

Table 1 Limits of Fluid Law

6. MODEL APPLICATION

In this section, we illustrate the working and scalability of SMM by using the PG concept to describe population movement through different geographical topologies. Prior to tackling user movement for these two network configurations, we highlight the architecture of our mobility simulator.

6.1 Simulator

The architecture of our simulator is a discrete event handler which is driven by the HLPPS algorithm.

At the initialization process, the simulator identifies the service area under consideration and interconnects the PGs together based on the angular connectivity. The simulator then determines the population of mobile users in each class of mobility at each PG and fixes a time stamp for that class of mobility, thereby initiating an event. Each event is en-queued in the event handler at its proper time and when the time of the event expires, movement of users from one PG to another occurs. When a mobile enters a new PG, the simulator retrieves its corresponding class of mobility and a comparison is made with the attraction weight of the strongest class of mobility at that specific PG. Consequently, if a mobile user in the Residence class enters a PG in the *Business* environment during the busy hour, based on the comparative test, the simulator decides whether the mobile user changes its class of mobility independent of it previous class history. This change also suggests that the user will have different calling behavior as well.

Once a movement is initiated, the simulator translates them into simulation statistics which relate to each mobile's `ID`, its previous and present class of mobility as well as its previous and present `x` and `y` co-ordinates and `velocity`. These statistics are collected in an output file for analysis.

6.2 City Area Model of Avon District

Figure 6 shows the City Area Model of Avon district, UK which covers a 40 km by 40 km area and shows the logical placements of the PGs in the four area types: City Centre, Urban, Suburban and Rural and their respective environments.

6.2.1 User Movement over City Area of Avon

During our three hour simulation period starting at 7.00 am, we have assumed a sample of 10,000 mobile users which were distributed in the different area zones and environments. Figure 7 shows mobile user distribution over the City Area Model of Avon.

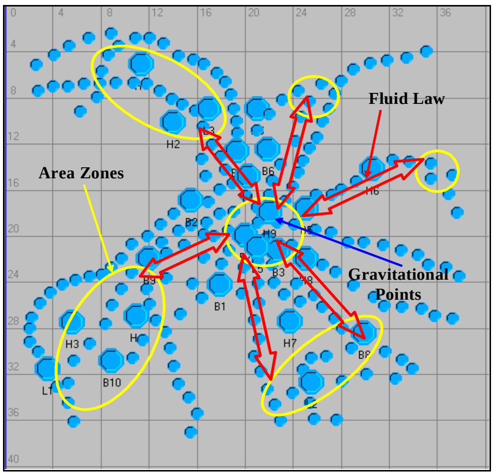

Figure 6. Pole of Gravity Concept applied to characterize movement for the City Area Model of Avon, Bristol ,UK

At the start of the simulation, about 35% of the population of mobile users is located in their residential environments in the Suburban area as depicted in Figure 7. As the attraction of the places change, population movement is initiated and subscribers move from one environment to another. Figure 7 clearly illustrates that this movement is initiated in a well defined fashion i.e. mobile users will move from the Rural and Suburban areas zones from the *Residential* environments towards the Urban and City Centre where the *Working* environments have been assumed to be located. At the end of the simulation, most of the mobile users are present in the *Working* environment found in the urban regions.

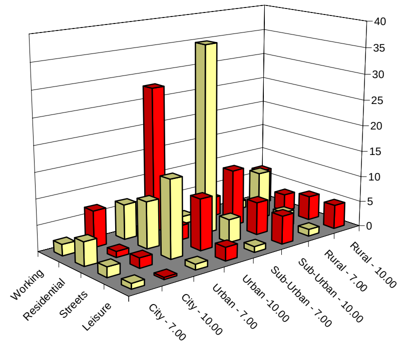

Figure 7. Mobile User Distribution over the City Area of Avon, UK

6.3 City Centre of Bristol

To illustrate the scalability of the model, we have applied SMM to the City Centre of Bristol which has an extension of 8 km by 8 km as shown in Figure 2. For comparison of the level of granularity, the area indicated in Figure 2 is equal to 4 of the squares in Figure 6, showing how detailed movement can be modeled by the PGs. The behavior of 1700 mobile users is characterized for a three hour period ranging from 7.00 a.m. to 10.00 a.m.

6.3.1 User Movement in the City Center of Bristol

At the start of the simulation, the *Residential* class of mobility has been assumed to be dominant as compared to that of the *Business* and *Others* in the different environments.

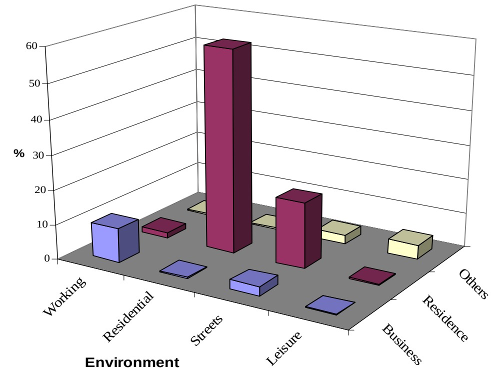

Figure 8. Spatial Distribution of Subscribers at 7.00 a.m.

The corresponding spatial distribution of subscribers at 7.00 a.m. in the morning is shown in Figure 8. The majority (60%) of the 1700 subscribers are located in their *Residential* environment and in their Residential class of mobility. As time proceeds, the strength of attraction of the PGs varies according to its class of mobility. This property is embedded in each and every PG and is dictated through the attraction function. A change in the attraction function causes the class of mobility of the *Business* and *Others* at the PGs located into the *Business* and *Shopping* environments to be more attractive. The fluid law initiates population movement towards these PGs and at the same time, a change in the attraction causes the gravity law to constantly re-calculate the steady state value of each class of mobility and fix their time of departure.

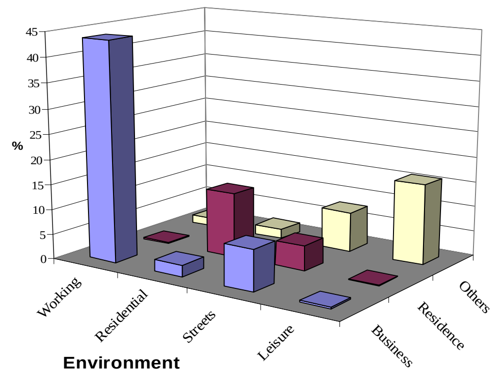

Figure 9. Spatial Distribution of Subscribers at 10.00 a.m.

This stochastic process enables the description of a realistic set of paths undertaken by subscribers in their respective classes of mobility. When the busy hour is reached at 10.00 a.m., about 40 % of the subscribers are located in the *Working* environment and in the Business class of mobility as shown in Figure 9 and this process is consistent with a daily life scenario.

7. EFFECT OF ACCURATE MOBILITY MODELING IN RADIO PLANNING

To illustrate the effect of accurate mobility modeling in radio planning of mobile networks, we evaluate the performance of SMM with the well known Random Waypoint (RWP) model by looking at the channel utilization and handover.

7.1 System Level Simulator

The system level simulator [11] consists of two main modules which run separately: Mobility Module and the Enhanced Data Rates for GSM Evolution for General Packet Radio Service (EGPRS) simulator shown in Figure 10.

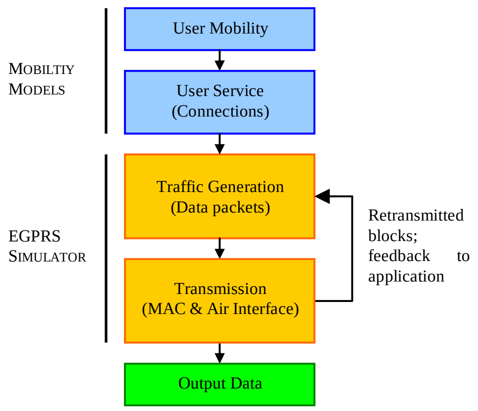

Figure 10. System Level Simulator

The EGDE radio interface is a new Time Division Multiple Access (TDMA) – based radio technology for GSM systems and reuses the GSM carrier bandwidth and time slot structure. Therefore the events generated in the simulation process can either occur for every burst, frame or super frame and can also be triggered by other dynamics in the system for instance the movement of a mobile updating its position or the initiation/termination of a call. All these events are placed in an event queue and they are performed one event at a time.

7.1.1 Simulation Parameters

The system level simulator is superimposed over the geographical framework of the City Centre of Bristol. Subscriber mobility for 1700 users for a three hour simulation starting from 7.00 a.m. to 10.00 a.m. is characterized by the SMM (the same mobility trace generated in Section 6.3 has been used) and RWP mobility models while deployment of the fixed cellular infrastructure is done on a regular hexagonal cell layout structure.

The simulation assumes a regular hexagonal cell layout structure with a frequency reuse of size four giving rise to a 41 BS configuration deployed for this scenario. The EGPRS simulator uses 200 kHz carriers with each carrier divided in time domain into eight time slots, assumes 3 carriers per cell and each BS has a frequency reuse of cluster size of four and the cell radius is assumed to be 1 km. For this particular scenario, the cellular network has been assumed of supporting only packet voice service. Independent of any movement determined by the mobility models, voice service calls may be initiated by the subscribers expressed in terms of call arrival rate. In order to provide the same traffic loading conditions on the cellular network for both mobility models i.e. SMM and RWP, the same call arrival rates was used in both cases while investigating the performance comparison.

7.2 Simulation Results

7.2.1 Aggregate Cell Traffic Distribution

The effect of an accurate mobility pattern characterized by the SMM with RWP in regards to channel utilization is shown in Figure 11.

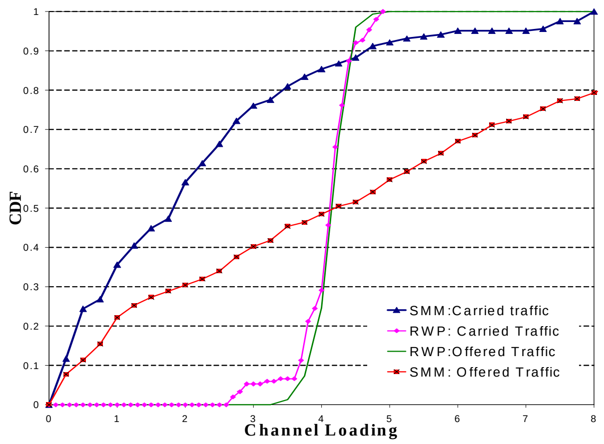

Figure 11. CDF of Aggregate Cell Traffic Distribution [6]

The key point shown in this graph indicates that the RWP model introduces too much diversity into the system and consequently overestimates capacity. With the SMM model, some cells consistently have more traffic, and therefore drop packets since the channel allocation pattern assumed in the simulation study is uniform. Consequently, more resources are required than there are available. This important effect is completely missed in the case of the RWP due to the fact that user distribution over the service area is uniform resulting in a fairly uniform traffic distribution. Therefore the carried load is always well inside the capacity region, resulting in less voice packets dropped. Therefore in the case of the RWP, the carried load CDF curve almost matches that of the offered load CDF.

Another important feature of Figure 11 refers to the shape of the CDF curves. In the case of the RWP model, the CDF curves for the offered and carried traffic follow a linear normal distribution where as in the case of SMM, both these two CDF curves approximate a log normal distribution of cell loading which effectively matches real traffic measurements from existing mobile systems [12]. Furthermore, RWP predicts no loss in traffic whereas in the case of the SMM, the overall traffic losses are about 20% for the same loading confirming the fact that mobility has a significant effect on the results.

7.2.2 Handover Distribution

Handover procedure involves the rerouting of a subscriber already involved in a call from one BS or channel to another and is highly dependent on the temporal behavior of mobile users. This process involves significant amounts of signaling and should be addressed with care in order to enhance capacity and signal quality of mobile systems.

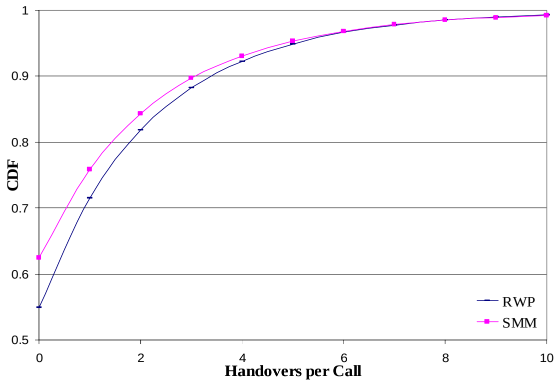

Figure 12. CDF of Handover

Figure 12 illustrates the performance comparison between the mean number of handovers per call using RWP and SMM for the City Centre of Bristol scenario. One can observe that RWP overestimates the number of handovers per call as compared to SMM. The main reason behind this observation is the fact that the temporal behavior of each subscriber changes under the different mobility models due to the mobility factors embedded in SMM. Therefore in the SMM case, some cells are heavily loaded as compared to others, so that active mobiles cannot handover to them and thereby restricting these active mobiles within their existing cell. This situation causes the subscribers to receive poor signal quality, which results in the termination of the call shown in the packet dropping statistics illustrated in Figure 11.

Handover is important for mobile system design because it is very disruptive from the point of view of quality and requires significant signaling and management. Random mobility models overestimate handovers which can lead radio planning engineers to think that they would require more signaling capacity than is actually the case.

8. SUMMARY & FUTURE WORK

In this paper, we have introduced a novel Scalable Mobility Model (SMM) which exploits the results of the HLPPS algorithm to introduce a stochastic system referred to as the PG. The PG assigns subscribers into specific classes of mobility based on their mobility characteristics and takes into account important mobility factors such as attraction points and geographical environments to enhance the concept of conscious traveling.

As a first step, to show the scalability of SMM to describe the spatial and temporal behavior of mobile users and its use as an efficient planning tool, we have illustrated user movement for the City Area Model of the Avon District and the City Centre of Bristol, UK each having a geographical extension of 40 km by 40 km and 8 km by 8 km respectively. We have shown that by taking into account mobility factors, we are able to describe a realistic set of daily patterns which were validated through simulation. Finally, we have compared our mobility model against the well known RWP model and simulation results show that accurate mobility modeling does have a significant effect on channel utilization and handover. This indicates that the choice of a mobility model is crucial in performance analysis of the mobile environment. This study also shows that random models were useful tools in the investigation of performance issues in the first and second mobile generation systems but with the continued increase in user penetration, more realistic mobility models have to be considered while investigating different mobility and radio resource management schemes [14].

The ability and simplicity with which the proposed mobility model, SMM, is able to implement real life population mobility patterns suggests that SMM stands as a better candidate to investigate performance issues of current and future wireless networks.

9. ACKNOWLEDGMENT

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