

# Scalable Mobility Model (SMM): A Concept for Optimum Radio Resource Planning for Wireless Cellular Network

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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 as Scalable Mobility Model, SMM, characterizes user movement at both individual and aggregate level and provides a realistic set of paths traversed on a daily basis by populating individual mobile users into specific mobility classes based on their mobility characteristics, attraction points, geographical environments and time factors. These features are implemented in SMM through a novel concept: the Pole of Gravity and our mobility model has been decomposed into three processes referred to as the physical, gravity and fluid sub-models. Using this new approach, we show how SMM can efficiently characterize user mobility for the geographical areas of the City Area Model of Avon District and the City Center of Bristol, UK having an extension of 40 Km by 40 Km and 8 Km by 8 Km respectively. Using this approach, we also show the need to take into account the spatial and temporal behavior of mobile users to deploy the non-moving elements of the cellular network in an optimum and efficient way for the service areas of Avon and Bristol, UK.*

*Keywords— Mobility model, teletraffic models, cellular network planning*

## 1. Introduction

A fixed network can be viewed as a collection of communication devices connected to network attachment points for a long time. By contrast, a wireless communication network may be viewed as a (very large) number of roaming mobile users who

continually change point of contact with the network within short time scales. Users' migration through the different radio environments constituting the mobile service will greatly affect the aggregate traffic observed at any point, as well as generating a considerable amount of mobility related signaling on the radio link. Given the scarcity of the wireless bandwidth coupled with the continued expected exponential growth of mobile users, new optimization techniques for efficient network planning are necessary for optimum allocation of network resources to manage user traffic and signaling load in future cellular networks. Consequently, radio-planning methodology has to be revised from area coverage (which was the main concern in first and second-generation wireless communication planning) to bringing the service to the user with the slogan "communicating anywhere, anytime with anybody" [1]. As such, subscriber mobility behavior will have a more acute effect on the planning and dimensioning of wireless networks.

Much research effort has been spent in the analysis of mobility patterns to characterize user mobility. In this context, different mobility models describing individual user behavior to aggregate movement flow with varied degree of implementation complexity have been proposed to investigate the issues related to mobility management and radio resource management. The need for different mobility models arises from the fact that these models suffer from limitations and can only approximate certain practical scenarios but fails to do so 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 corresponding ability to track mobile user on a per mobile basis.

The contribution of this paper is the introduction of this novel scalable mobility model, SMM, characterizing both individual and aggregate user movements at different levels of granularity in space and time. SMM provides a realistic set of paths traversed on a daily basis by grouping users having the same mobility characteristics into specific classes of mobility and introduces the concept of ‘attractivity points’ for specific locations which is time dependent through a heuristic ‘attractivity’ function. These characterizing features are implemented in our mobility model through the introduction of a stochastic node referred to as the Pole of Gravity. This stochastic system extracts the features of the head-of-the-line proportional processor sharing (HLPPS) fluid models [2] in order to populate mobile users in different classes of mobility based on their mobility characteristics and characterizes the spatial and temporal behavior of mobile users in a scaleable way. The modeling approach undertaken during the implementation of the SMM is based on three folds: 1) its ability to fit field data available by mobile network operators to validate its usage over a specific coverage and service area, 2) it is based on open multi-class queuing theory and as such allows the tracking of mobile users on a per user or aggregate basis and, 3) it is centered around a scaleable algorithmic mobility model that can be applied to a large number of possible horizontal environments, from wide area networks (WAN) to local areas networks (LAN).

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 concept of poles of gravity. In Section 4 we highlight our system model and give a detailed description of the physical, gravity and fluid sub-models. Section 5 gives an in-depth insight of the mathematical framework for the gravity and fluid laws, which relies on the results of open multi-class queuing networks and fluid equation respectively. Section 6 shows the application and scalability of the SMM and its ability to describe user movement behavior for the City Area of Avon and the City Center of Bristol, UK. Section 7 illustrates the use of the traffic map to optimally allocate the radio resources. Finally Section 8 concludes the paper and outlines the scope for future work.

## 2. Probing the Literature

In general, user mobility models attempt to describe human movement behavior, either as an individual or a set of individuals at different levels of granularity in a geographical environment.

Simple models based on Brownian motion [3] and Markovian models [5] characterize individual user behavior by assuming that the transitional probability states of user movement are known *a priori* while aggregate population movement has been well characterized using the fluid [4] and gravity models [8]. In [7], a stochastic model for mobility called the Markovian highway *Poisson-Arrival-Location Model* (PALM) is introduced and developed rigorously. This model uses a pair of differential equations characterizing the movement of calling and non-calling vehicles and the model can be viewed as a traffic demand to describe the dynamics of a mobile network.

The eventual goal of mobility models are to predict the daily movement of mobile users in terms of the amount of time spent at a particular location and the number of cells crossed as accurately as possible. To enhance the above mentioned existing mobility models, researchers have observed the need for combining mobility modeling and transportation theory [6, 8] to estimate performance issues of a mobile network in a predefined service the area. In [8] variations of a gravity model have been used to characterize aggregate movement behavior through *national* and *international* mobility models exploiting the transport traffic data. A similar approach was undertaken in [9] where the researchers captured the effect of mobility on traffic parameters at different granularity in space by introducing a set of mobility models describing population movement through city, zone and street level.

While these enhanced models are rich and expressive within the context of transportation modeling, they are unnecessarily over-detailed at a topographical level as a basis for creating event patterns that allow performance analysis of a mobile network. Furthermore, users with mobile terminals are less constrained by the transport network, which, in fact is absent in many short-range built-environment scenarios. Finally, it has been argued that there is a degree of independence of scale related to cell size and signaling traffic that requires us to examine small population as much as mass movements.

What is required is a scaleable algorithmic mobility model that can be applied to a large number of possible network configurations.

### 3. SMM: A New Approach for Predicting & Tracking User Mobility

This section starts with the motivations and contribution behind our work in this paper and is followed by the introduction of the novel concept of Pole of Gravity to describe the temporal and spatial behavior of population movement in a scalable way.

#### 3.1 Motivations

Our approach to describe user movement behavior is primarily motivated by the following observations:

1. The analysis of user mobility has been formulated by a vast number of researchers to describe population movement behavior on either an individual or aggregate basis but never as a combination of both as the use of these models were either focused on looking at specific issues such as location management or teletraffic. In our modeling approach, we have exploited the features of a fluid model [2] to characterize mobile user displacement at both microscopic and macroscopic level of granularity. The microscopic level is characterized by the *Brownian Movement Model* through a diffusion process while the macroscopic level is achieved by the aggregation of individual user movement to characterize the movement of mass.
2. A realistic mobility model should capture a set of most probable paths traversed by subscribers on a daily basis taking into the demographic and geographical information of the region under consideration. As such it is important to define individual user profile having specific mobility and call patterns. We have introduced those key factors in our model by using the gravity model in a special form and defining individual user profile having same mobility characteristics, divided the geographical areas into different environments whose attraction strength varies with time according to its class to generate a realistic set of paths undertaken for a specified topology.
3. To the best of our knowledge, we have not come across any mobility models that have been used to characterize user mobility at

different granularity in space. Instead, most of the works related in this field concentrate on refining the model for a particular network scenario. The main motivation and challenge behind the implementation of SMM, was to provide a scalable algorithm that can be applied to a number of possible horizontal environments while retaining its ability to predict user movement behavior taking into account the key factors of mobility. Using the concept of open multi-class queuing theory, we introduce a novel technique referred to as the Pole of Gravity to characterize the spatial and temporal behavior of subscribers for different cellular network configurations.

#### 3.2 Pole Gravity (PG)

The core technique for the modeling of spatial and temporal population movement behavior in SMM, is achieved by discrete stochastic nodes referred to as Pole of Gravity. This stochastic system exploits the results of open multi-class queuing networks and extracts the key features of the family of the head-of-the-line proportional processor sharing (HLPPS) fluid models [2] to populate mobile users in different classes of mobility by taking into account several important factors of mobility.

A Pole of Gravity represents a geographical location that contains a mass of mobile users and continually calculates the population of the users for each class of mobility with respect to the location's attractivity and time. This stochastic node conceptualizes the following aspects:

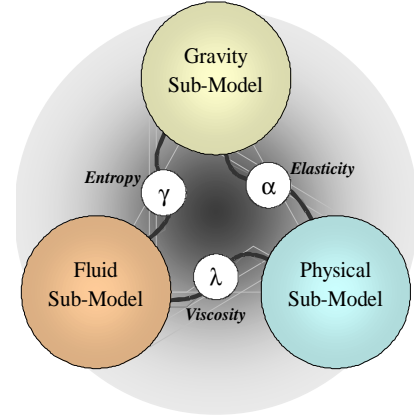
- **Classes of Mobility** – Mobile users having the same mobility behavior are grouped into a specific class of mobility. The corresponding class of mobility also reflects mobile users' calling behavior and use of services. For our model, three classes of mobility have been considered: *Business*, *Residential* and *Others*.
- **Area Zones** – The scalability of the pole allows the investigation of mobile user movements at different granularity in space. The horizontal environments under consideration have been categorized into different geographical areas ranging from City Area Model to the City Center. For the City Area Model, the topological area has been divided into four area types: *City Center*, *Urban*, *Sub-Urban* and *Rural*. Using the same model, user mobility can be defined at a more refined granularity in space. As such focusing on only one area type, user movement and its corresponding calling behavior can also be investigated for the City Center and this specific area type has been divided into four

environments: *Working, Residential, Shopping and Streets*.

- **Attractivity Points (APs)** – Represent locations that attract users with a specific mobility class and at which individual users of that class spend a considerable amount of time. The strength of attraction to any pole varies during the day for each class of mobility and is a function of time. For instance, office premises would attract a large flow of subscribers during morning hours and outflow during evening hours. 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 ‘attractivity’ of the area zone environment at specific time of the day. This attraction factor can be decided only heuristically on the basis of knowledge of typical daily traffic peaks which can be easily be fed in the model.
- **Time Periods** – In the context of a wireless network, three time periods can be identified for a day during which certain types of movements take place. The first one is the *rush hour* (RH) characterizing the movement of mobile users from/to the city center where most business establishments are concentrated or to/from the outskirts where most residential areas are located. The second time period is the *busy hour* (BH) where the subscribers reside at certain APs (e.g. work places) for a considerable amount of time and finally the *off peak hour* indicating minimum usage of the wireless network by mobile users [10]. These three factors can be easily included in our mobility model.

## 4. System Model

SMM is based on the integrated design of three processes: *Physical Sub-Model*, *Gravity Sub-Model* and *Fluid Sub-Model* which forms our system model.



**Figure 1: System Model**

This enhanced concept provides some interdependencies between the three sub-models through the coefficients of *elasticity*, *viscosity* and *entropy* as illustrated in Figure 1.

### 4.1 Physical Sub-Model

The configuration of the physical sub-model proceeds in the following steps:

1. It identifies the topology by dividing the geographical area under consideration into different area zones (City Center, Urban, Sub-Urban and Rural) and locates the positioning of the Poles of Gravity into specific environments (Working, Residential, Shopping and Streets).
2. One of the approaches taken under consideration while modeling SMM, is that geographical and demographical information obtained from land surveys can be easily incorporated for the validation of the model and this process is done at the physical sub-model level. Based on the logical placement of the poles, the initial population density of each class of mobility (i.e. Business, Residential & Others) is defined. These initial values have been configured in the model based on the cartographic data of the terrain under consideration. For instance the population density of mobile users in the residential class has been assumed to be sparse in the urban and city center for the business environments as compared to the rural and sub-urban for the residential environments when configuring the model.
3. Each pole of gravity is divided into  $R$  equal sectors and the minimum distance criterion has been used for interconnecting the poles together. These interconnections represent the most probable paths undertaken by mobile

users during movement. At the start of the simulation, mobile users are assumed to be uniformly distributed over the poles and the spatial distribution the mobile users is given by Equation 1:

$$z = r e^{i\theta} \quad (1)$$

where  $r = \begin{bmatrix} 0, \sqrt{\frac{S}{\pi}} \end{bmatrix}$  and  $\theta$  is uniformly distributed over  $[0, 2\pi]$ .

An illustration of the physical sub-model is shown in Figures 4 and 6 for the City Area Model of Avon District, and the City Center of Bristol, UK each having an extension of 40 Km  $\times$  40 Km and 8 Km  $\times$  8 Km respectively.

#### 4.2 Gravity Sub- Model

Gravity models are based on the assumption that population movement from a given point to another is directly proportional to the attraction of the area and inversely proportional to the distance of separation between them. Thus, the number of users present at a specific location is dependent on the attractivity of the location.

Our gravity sub-model has three main functions. Firstly, it extracts some properties of gravity models to populate mobile users in their respective class of mobility by taking into account the ‘attractivity weight’ of each mobility class in a specific environment through the ‘attractivity function’. Secondly, it dictates the temporal behavior of individual mobile user with respect to their mobility class. This process is an enhancement of open multi-class queuing networks more specifically on a family of processor sharing fluid models referred to as the head-of-the-line proportional processor sharing (HLPPS) fluid models. By using the results of queuing theory, this sub-model characterizes the concept of stability and this sub-model constantly calculates the attraction of all the poles of gravity in order to achieve convergence towards a stochastic equilibrium.

Using the above features, we have included the principle of HLPPS in the pole of gravity and have considered each class of mobility as a waiting queue having an infinite capacity. The length of the queue changes dynamically depending on population movement from one class of mobility to another which is influenced by the changes in the ‘attractivity function’ with time.

This stochastic process is governed by the ‘gravity law’ detailed in our mathematical framework.

#### 4.3 Fluid Sub- Model

Fluid models are continuous and conceptualize population movement as movement of mass rather than individual movement patterns [4] on a macroscopic level.

Our movement model exploits the features of the fluid model to characterize mobile user displacement at both microscopic and macroscopic level of granularity. The microscopic level is characterized by the *Brownian Movement Model* through a diffusion process while the macroscopic level is achieved by the aggregation of individual user movement to characterize movement of mass. Individual user movement is initiated from pole to pole based on the strength of attraction of each mobility class dictated by the ‘attractivity function’ defined in the *gravity sub-model*. During this process, as the mass moves through the topological area under consideration determined by the *physical sub-model*, and in the process, the subscriber may or may not change its class of mobility independent of its class history.

Taking into account the important factors of mobility and distance, this process is responsible to provide a realistic sets of paths undertaken by mobile users characterized through the ‘transitional probability matrix’ and governed by the *fluid law*.

#### 4.4 Interaction between Sub- Models

Summarizing the motivations of SMM, are to describe user mobility at an individual movement level through a realistic set of paths traversed on a daily basis and at the same time implement a scalable algorithmic mobility model that can be applied to a large number of possible cellular network configurations.

To implement such an algorithm, we have provided an interaction between the physical, gravity and fluid sub-models as shown in Figure 1 through the coefficients of *elasticity*, *viscosity* and *entropy*. The physical meaning of these coefficients in the context of our model is best explained by considering the movement of mass of users when applying the model to a cellular communication system. The routes traversed by mobile users through different environments having specific ‘attractivity strength’ are overlaid by poles of gravity on different geographical framework as illustrated by Figures (4) and (6). The physical and gravity sub-models characterize these features. Using the analogy of fluid models [2], we replace individual user mobility characterized by our Brownian Movement Model by the concept of

‘mobile user mass’ by looking at population movement at a macroscopic level of movement flow. This user mass can be of any type of class of mobility, which changes, as the mass moves through the predefined coverage area. In accordance with the underlying queuing theory, this mobile mass moves from one pole to another and this movement is controlled through the coefficients of elasticity, viscosity and entropy.

The coefficients of *viscosity* ( $\lambda$ ) and *entropy* ( $\gamma$ ) governs the fluid law. As the fluid moves from one pole to another, the coefficient of viscosity provides a perception of distance between the two poles of the originating user to its destination. Variation of this parameter has the effect of altering the distance covered by the fluid flow, as such controlling the speed of the fluid flow. This causes the fluid flow to either expand or compress and the rate at which this process occurs is controlled by the coefficient of elasticity. In other words, the coefficient of elasticity determines the rate at which the mass of mobile users will flow from one pole of gravity to another characterized by the ‘gravity law’. Based on this temporal behavior, the circulation of the fluid mass from one pole to another follows the law that is between a deterministic or random process. The coefficient of entropy acts on the degree of randomness of the process introducing a degree of friction between two poles when a change of attraction occurs. The coefficients of viscosity and entropy are characterized by the fluid law and defined through an accompanying fluid equation which takes into account the distance factor and attractivity weight.

Following the above explanation, we can therefore give fundamental meaning to the parameters of elasticity, viscosity and entropy. The coefficient of elasticity is defined as the model’s reactivity to restore equilibrium when a change in attraction occurs among the Poles of Gravity. Entropy is a measure of introducing a degree of friction between two different poles while the coefficient of viscosity gives a perception of distance between two zones of the originating mobile to its destination. A more detailed insight of how the variation of these parameters affects user movement of the model is provided in the next section.

## 5. Mathematical Framework of SMM

This section highlights the mathematical framework on which the gravity and fluid sub-models are based. We first provide the general notation used in the configuration of SMM and formulate the concept of the ‘gravity law’ which has the responsibility of populating individual subscribers in different classes of mobility based on the dynamics of their locations, control the temporal behavior of the users and monitor the stability of the system. Finally the ‘fluid law’ defines our fluid equation characterized by a ‘transitional probability matrix’ which governs population movement through the system at both a macroscopic and microscopic level.

### 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 geographical area under consideration
R	Angular connectivity
$\alpha$	Coefficient of elasticity at Pole of Gravity $(PG_j)$ and $\alpha_j \in [0,1]$
$\gamma$	Coefficient of entropy at Pole of Gravity $(PG_j)$ and $\gamma_j \in [0,1]$
$\lambda$	Coefficient of entropy at Pole of Gravity $(PG_j)$ and $\lambda_j \in [0,1]$
$A_j$	Mean Sojourn Time in $PG_j$
$S_j$	Surface area over which mobile users of any class of mobility is distributed in the $PG_j$
$D_{j,K}$	Density of mobile users for class of mobility K, where $K \in (\text{Business, Leisure, Shopping, Residential})$ for $PG_j$
$Att_{j,K}(t)$	Attractivity weight for class of mobility K for $PG_j$ during simulation time t and $is \in [0,1]$
$l_{j,K}(t)$	Current number of mobiles in class of mobility for $PG_j$ at time t

### 5.2 Gravity Law

The ‘Gravity Law’ defines three important properties in the model: 1) characterization of mobile users in different classes of mobility, 2) their corresponding temporal behavior and 3) stability of each class of mobility. These three

features are detailed in the following sub-sections below.

### 5.2.1 Mobile User Characterization

This property populates the users at the poles in different mobility classes where each class of mobility is assumed to be a waiting queue having an infinite capacity. The ‘gravity law’ takes into account the density of the users in that class,

$D_{j,K}$ , their corresponding attractivity weight and surface area over which the users are distributed. This process is executed each time a change in the ‘attractivity weight’ occurs. As such, the gravity sub-model constantly re-calculates the steady state value of the total number of mobile users in each class of mobility,  $C_{j,K}(t)$ , through Equation 2

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

where  $M$  is the total number of mobile users and  $P_{j,K}(t)$  is referred to as the penetration matrix function of users for each mobility class in their respective environments and is defined by

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

$N$  and  $O$  represents the total number of poles of gravity and mobility classes respectively.

Equation 3 introduces a method for estimating the number of users at specific locations and populates them into their respective classes of mobility by taking into account their mobility characteristics which is inherited through the attractivity strength of the mobility class in that environment. This approach provides a simple and efficient way to fit field results from official topographical cartographic database or mobility traces available from operators and generates a penetration matrix characterizing the individual penetration weight for a class of mobility,  $K$  at a specific pole. As such, when a change in attraction occurs at a specific location, this matrix will change accordingly generating different penetration weight for the locations and classes of mobility as calculated by Equation 3. This in turn allows the re-calculation of the number of mobiles in each mobility class at each location through Equation 2..

### 5.2.2 Temporal Behavior

The departure process of mobiles from one pole to another is determined by the inter-departure time. When a mobile enters a Pole of Gravity, it is assigned a residence time and when this time elapses, its new destination is chosen based on the ‘attractivity’ of surrounding poles and distance factors governed by the *fluid law*.

The gravity sub-model is an enhancement of the HLPPS algorithm and, this discipline of fluid models 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 [2]. As such, the fraction of time spent by a mobile in a specific pole 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:

$$ID_{j,K}(t) = A_j \alpha_j^{\phi_{j,K}(t)} \quad (4)$$

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

$$\phi_{j,K}(t) = \frac{l_{j,K}(t) - 1}{C_{j,K}(t)} \quad (5)$$

Equation 4 shows indicates that the coefficient of elasticity controls the rate at which mobiles enter and leave a pole. At the initialization of the simulation,  $C_{j,K}(t)$ , and the current number of mobiles,  $l_{j,K}(t)$ , are assumed to be equal (where  $C_{j,K}(t) \gg 1$ ) such that  $\phi_{j,K}(t) \approx 1$ .

### 5.2.3 Stability

To characterize the concept of stability in our model, we have used a similar approach based on the *positive Harris recurrent* terminology detailed in [2]. This concept is best illustrated in Figure 2. Considering Equation 4, for a particular CM,  $K$ , in pole of gravity  $j$ , three states can be identified as defined below:

1.  $ID_{j,K}(t)$  decreases from  $A_j$  to  $A_j \alpha_j$ ,  $0 < l_{j,K}(t) <$

$$\begin{aligned}
 & C_{j,K}(t) \Rightarrow 0 < \phi < 1 && j,K(t) \\
 2. & ID_{j,K}(t) = A_j \alpha && j : \\
 & l_{j,K}(t) = C_{j,K}(t), \Rightarrow && \\
 & \phi && j,K(t) = 1 \\
 3. & ID_{j,K}(t) \text{ decreases from} && \\
 & A_j \alpha && j \text{ to } 0, l_{j,K}(t) > \\
 & C_{j,K}(t) \Rightarrow \phi && j,K(t) > 1
 \end{aligned}$$

Figure 2: General representation of stability conditions for a mobility class, K, at Pole of Gravity j

Referring to the **Critical** in [2], condition 1 is referred to as strictly *sub-critical* while condition 2 is referred to as *critical* condition and 3 is defined as *super-critical*. At the start of the simulation, the model is assumed to be in stochastic equilibrium since  $\phi$  is assumed to be in  $l_{j,K}(t)$   $j,K(t) \approx 1$ . When a change of attractivity occurs in a particular queue at a specific pole, the equilibrium of that pole is altered due to a change in the value of  $\phi$   $j,K(t)$ . The gravity law will re-calculate the number of mobiles in each queue with the aim to converge towards the equilibrium state. Convergence towards this point is dependent on the coefficients of elasticity and entropy. The coefficient of elasticity defines the rate of the convergence process as identified by Equation 4 while the coefficient of entropy affects the reactivity of the convergence by controlling the movement of mobiles from one pole to another in an predefined fashion and as such will determine the current number of mobiles,  $l_{j,K}(t)$  and hence the value  $\phi$   $j,K(t)$  as defined through Equation 5.

This process is characterized through the fluid law which is detailed in the next section. The above concept shows the dependency between the gravity and fluid sub- models.

### 5.3 Fluid Law

In its simplest form, a fluid model is only useful for macroscopic movement [4] and can be approximated by a corresponding Brownian system model to mimic the behavior of mobiles at a microscopic level.

Our fluid sub- model extracts the concepts of the fluid and Brownian models to fix the law of circulation of mobile users by considering user displacement among the poles of gravity defined through physical sub- model. This process is governed by the fluid law and is embedded in each and every pole of gravity through our fluid equation characterized by a transitional probability matrix which takes into account the factors of ‘attractivity strength’ of that mobility class and distance.

#### 5.3.1 Mobile User Movement

When the inter- departure time of a specific mobility class, K, in  $PG_i$  expires determined by Equation 4, user movement from this pole to the surrounding poles is initiated through the transitional probability matrix defined by Equation 6 and has the following properties:

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

$$P_{i,KL}(t) = \gamma_i^{th}(\Delta_{ji}(t)) \quad (6)$$

Equation 6 gives an insight of how the physical and fluid sub- models interact with each other. At the initialization of the simulation,  $PG_i$ , interconnects with its neighboring poles through the angular connectivity,  $R$  and identifies the sets of  $L$  ( $L \in [0, R]$ ) most probable paths that mobile users will take during movement. This movement is enhanced by taking into account the mobility factors defined by the gravity sub- model through the attractivity weight of each class of mobility and is expressed in Equation 6 through  $\Delta_{ji}(t)$ . Another important property of our fluid equation is that the coefficients of entropy,  $\gamma_i$ , and viscosity,  $\lambda_i$  will determine the movement of the users from one pole to another. While  $\gamma_i$  controls the behavior of mobiles based on the strength of the mobility class of users, the

coefficient of viscosity fixes the movement of users based on the distance factor. This property allows the reuse of the pole of gravity concept to describe population movement for different geographical areas in a scalable way for different set of scenarios.

Using the above approach, we have been able to use a simple and efficient way of characterizing user displacement for each pole of gravity.

## 6. Model Application

In this section, we illustrate the working and scalability of SMM by using the pole of gravity concept to describe population movement through different geographical topologies ranging from the City Area Model of the Avon district, UK to the City Centre of Bristol, UK.

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 shown in Figure 3 and is a discrete event handler driven by the HLPPS queue model.

At the initialization process, the simulator identifies the geographical topology under consideration specified by the physical sub-model and interconnects the poles of gravity together through the minimum distance criterion based on the angular connectivity. The simulator then determines the population of mobile users in each class of mobility at each pole and fixes a time stamp for that mobility class thereby initiating an event. Each event is enqueued in the event handler at its proper time and when the time of the event expires, movement of users from one pole to another dictated through the fluid law is initiated. When a mobile enters a new pole, the simulator retrieves its corresponding class of mobility and a comparison is made with the 'attractivity weight' of the strongest class of mobility at that specific pole. Consequently, if a user in the residence class enters a pole in the business environment during the busy hour, based on the comparative test, the simulator decides whether the user changes its class of mobility independent of its previous class history. This change also suggests that the user will have different calling behavior as well.

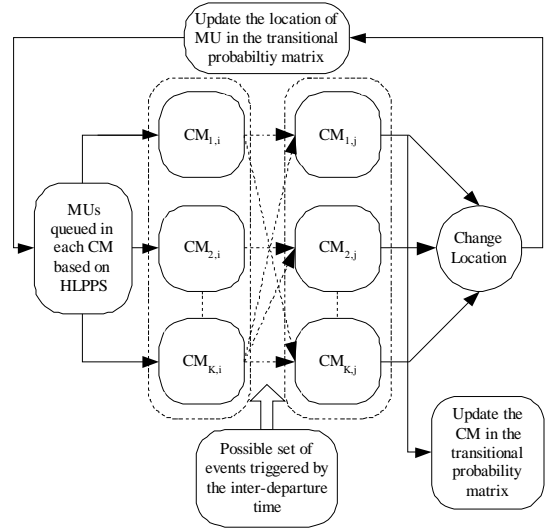
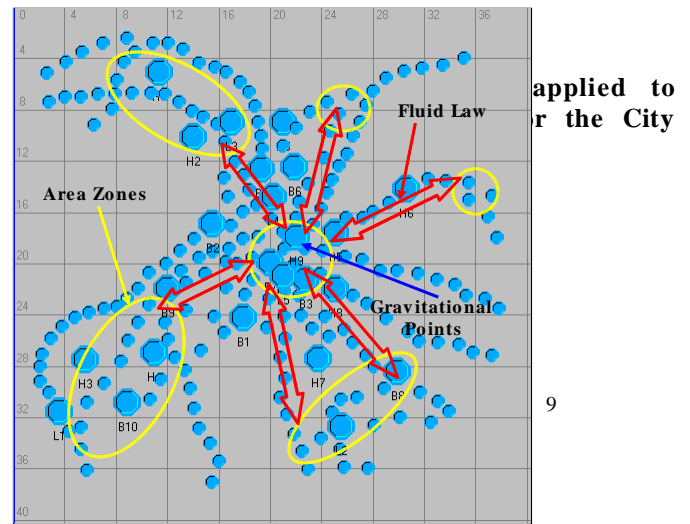


Figure 3: Mobility Simulator Architecture

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 in kilometers and its velocity. These statistics are collected in an output file for analysis at the end of simulation.

### 6.2 City Area Model of Avon District

Figure 4 shows the City Area Model of Avon district, UK and the depicted region has an extension of  $40 \text{ km} \times 40 \text{ km}$ . The physical sub-model identifies the logical placements of the poles in the four area types: *City Center*, *Urban*, *Suburban* and *Rural* and their respective environments i.e.: *Business*, *Residential*, *Streets* and *Shopping*. The city center is surrounded by urban, suburban and rural areas with the rural area being the furthest. The gravity sub-model determines the number of mobiles in each class of mobility for the different environments through the gravity law based on their respective attractivity strength while the fluid law is responsible for population movement based on the attraction of the classes and distance factors.



### 6.2.1 Mobile User Movement in the City Area Model

During our three hour simulation period starting at 7.00 am, we have assumed a sample of 10,000 mobile users which was uniformly distributed in the in the different area zones and environments. Figure 5 shows mobile user distribution over the City Area Model of Avon and initially (i.e. at 7.00 am), most of the mobile users are situated in their residential environment found in the Sub-Urban area zone.

Movement of mobiles is initiated at the end of the inter-departure time for each mobility class determined through the HLPPS algorithm. When this time expires, the most probable path is chosen based on the fluid law. Upon entering a new pole of gravity, the mobility class of the mobile is retrieved and a comparison is made with all the classes of mobility present at the pole based on a uniform distribution. In this way, the mobile user may change its class of mobility and as such, the inter-departure of that specific class is recalculated through the gravity law. As such, a mobile user can change its class of mobility as well as its direction irrespective of its past history.

Based on the explanation, at the start of the simulation, about 35% of the population of mobile users is located in their residential environments in the sub-urban area as illustrated in Figure 5. As the ‘attractivity function’ of the places change, population movement is initiated and during this period of time, mobiles are going to move from one environment to another and Figure 5 indicates that this movement is initiated in a well defined fashion i.e. mobile users will move from the Rural and Sub-Urban areas zones from the Residential environments towards the Urban and City Center and at the end of the simulation, most of the

mobile users are present in the Working environment found in the Urban regions.

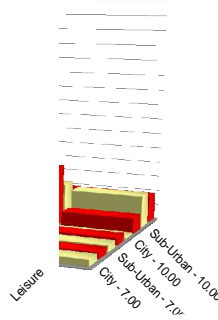
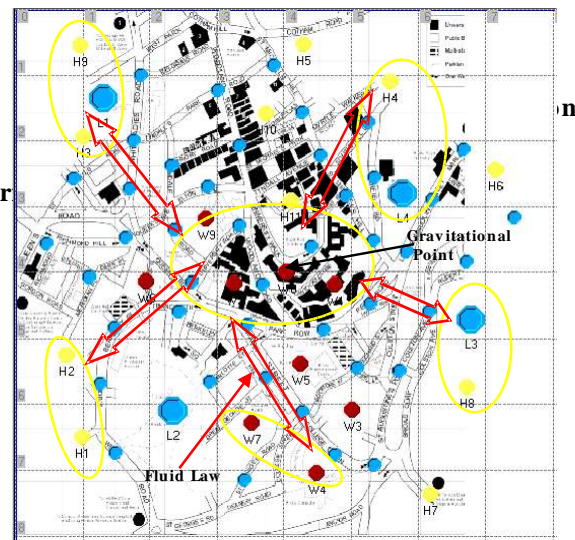


Figure 5: Mobile User Distribution over the City Area Model

### 6.3 City Center of Bristol

To illustrate the scalability of our model, we describe mobile user movement at a more refined granularity in space focusing on the City Center of Bristol which has an extension of 8 km × 8 km as shown in Figure 6. The realistic behavior of 1700 mobile users is characterized through the Business, Residential, Streets and Leisure environments for a three hour period ranging from 7.00 a.m. to 10.00 a.m.



#### 6.3.1 Mobile User Movement in the City Center of Bristol

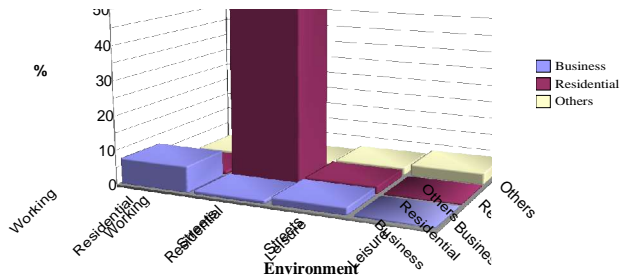


Figure 7 (a): Spatial Distribution of mobiles at 7.00 a.m.

Figure 7 (b): Spatial Distribution of mobiles at 8.00 a.m.

Figure 7 (c): Spatial Distribution of mobiles at 9.00 a.m.

Figure 7 (d): Spatial Distribution of mobiles at 10.00 a.m.

Mobile users are uniformly distributed over the City Center of Bristol and initially the attractivity of residence class of mobility is assumed to be dominant as compare to that of the business and others ‘attractivity strength’ class. Based on this factor, the gravity law populates mobile users in the residence class of mobility and the majority of those user are located in the residence environment as shown in Figure 7 (a). At the same time, the gravity law specifies the inter- departure for each mobility class at each pole of gravity.

As time proceeds, the strength of attraction of the poles of gravity varies according to its class and this property is embedded in each and every pole through the ‘attractivity function’. While defining this heuristic approach, we have taken into account the environment in which the poles are located and as such, as simulation time proceeds, the class of mobility of the *Business* and *Others* users in the poles located into the

business and shopping environments are made more attractive such that the fluid law will be responsible to initiate population movement towards these poles while the gravity law will constantly re- calculate the number of mobile users in each class and fix their time of departure in an attempt to keep the model stable.

The above stochastic process describes a realistic sets of path undertaken by each mobile and the aggregate movement is illustrated in Figures 7 (b), (c) and (d). These Figures indicate population movement from one particular mobility class to another as they are roaming through different environments. During the rush hour period, (7.00 – 9.00), the attractivity weight of the residential class decreases since mobile users start to move from their residential places and proceeds to work and in doing so, their change their mobility class in the process. When the busy hour is reach, most of the mobile users

are found in the *Working* environment and in the *Business* class of mobility which is consistent to a realistic sets of paths of individuals during a daily life scenario. This heuristic function can be further enhanced and make the model more accurate by using the knowledge of typical daily traffic peaks which are available from network operators.

## 7. Radio Resource Planning

## 8. Summary & Future Work

In this paper, we have introduced a novel scalable mobility model which allows the tracking and location of individual mobile users over a wide range of topological areas. The model is based on queuing theory and we have used the results of Head-of-the-Line Proportional Processor Sharing algorithm to introduce a stochastic system referred to as the pole of gravity concept. We have adopted a flexible modeling approach while designing the pole of gravity such that it is able to easily fit field results from demographic data or mobility traces available from operators to validate its usage over the specified coverage area under consideration.

This novel concept gives a good correspondence to user behavior, allowing the model to be used for 'what-if' type analysis with the introduction of new poles of gravity to characterize new environments in the existing network such as a new shopping centre, sporting event (e.g. a football match on a Sunday afternoon), creation of a Business park, etc. This concept introduces an efficient and easy planning methodology for mobile operators to access their network in order to meet the demand of their customers through a guaranteed Quality of Service (QoS) and at the same time allows operators to simulate different network scenarios in order to fine tune their network accordingly to cater for any change in the dynamics of their network.

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 pattern which was validated through simulation. Finally, we have demonstrated how the information extracted from SMM can be used to provide a direct mapping between user displacements into traffic demand.

We are currently expanding the use of SMM in order to investigate several issues related in the analysis of mobility management and radio resource management [11]. We plan to incorporate mobility traces from operators in order to validate the usage of SMM over different coverage area. This in turn will enable us to fine tune our mobility model and select the appropriate values for the parameters of elasticity, entropy and viscosity for different network topologies and different scenarios for instance the Rush Hour and the Busy Hour. The ultimate aim of our research is to develop a traffic prediction planning tool which will be able to self-adapt itself to the dynamic changes of a wireless networks taking into account user movement behavior which is overlooked by conventional mobile network planning tools such as PLANET [12].

## 9. Acknowledgment

The work reported in this paper formed part of the Work Area 2 of the Core 2 Research Program of the Virtual Center of Excellence in Mobile & Personal Communications, Mobile VCE, [www.mobilevce.com](http://www.mobilevce.com) whose funding support is gratefully acknowledged. More detailed technical reports on this research are available to Industrial Members of the Mobile VCE.

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