Mobility Modelling for Future Wireless Communications

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Abstract

This paper presents a mathematical framework of a mobility model for the prediction and tracking of mobile users. The model has been decomposed into three processes referred to as the *physical*, *gravity* and *fluid sub-models*. It also introduces the new concept of pole of gravity to characterise the spatial and temporal behaviour of mobile users. An investigation has been carried out to model user movements in the central area of Bristol for the peak period.

***Keywords*:** *Mobility model, teletraffic model, multimedia*

1. Introduction

Future wireless communication systems, such as . Universal Mobile Telecommunications System (UMTS) have promised to offer a wide variety of highly sophisticated communication services using the slogan "communicating anywhere, anytime with anybody" [1].

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 timescales. 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 signalling on the radio link and for mobility management purposes. Given the scarcity of the wireless bandwidth, optimisation techniques for efficient network planning are necessary for allocating network resources to manage user traffic and the signalling load. To address these issues, much research effort has been spent in the analysis of mobility patterns to characterise user mobility.

Mobility models attempt to describe human movement behaviour, either as an individual or a set of individuals at different levels of granularity in a geographical environment. They are involved in the analysis of (1) mobility management (location management and handoff) and (2) radio resource management.

Simple models based on Brownian motion [8], fluid flow [5] and also Markovian model [6] have been used to characterise user mobility. Uniform and fluid models cannot characterise individual mobile behaviour while the Markovian model assumes that the transitional probability states are known a priori. To refine these models, researchers have observed the need for combining the mobility modelling approach and transportation studies [15] to estimate performance issues for a mobile network service the area. In [12], 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 to describe the movement of vehicles. In [7] variations of a gravity model has been used to characterise aggregate movement behaviour through *national* and *international* mobility models exploiting the transport traffic data. A similar approach was undertaken in [2] where the researchers capture 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 models are rich and expressive within the context of transportation modelling, they are unnecessarily over-detailed at a topographical level as a basis for creating event patterns that allow teletraffic analysis of a mobile network for the purposes outlined above. 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 arguably a degree of independence of scale related to cell size and signalling traffic [10] that requires us to examine small populations 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.

In this paper we introduce such a mathematical framework for predicting and tracking mobile user behaviour in a wireless network by using the results of open multiclass queuing networks. Our model is extracts the features of the head-of-the-line proportional processor sharing (HLPPS) fluid models [11] in order to populate mobile users in different classes of mobility based on their mobility behaviour. We also introduce the new concept of pole of gravity to characterise the spatial and temporal behaviour of mobile users in a scaleable way.

The remainder of the paper is organised as follows. Section 2 discusses the main types of mobility models used in literature to describe user movement. In section 3, we present our modelling approach and introduce the concept of poles of gravity. Section 4 develops the mobility model and characterising features are discussed. Section 5 describes architecture of our mobility simulator architecture and presents simulation results of user density in space and time for the geographical area of Bristol. Section 6 discusses the integration of the mobility traces with a service model to illustrate terminal mobility traffic generated. Finally, section 7 concludes the paper and introduces future work.

2. BASIC TOOLS FOR MOBILITY

Before discussing the modelling approach that we have undertaken to develop our mobility model, we review common mobility models used in the literature to characterise aggregate and individual user movement behaviour.

2.1 Fluid Model

The fluid model [5] characterises aggregate population movement as flow of a fluid with their direction of movement uniformly distributed over [0, 2π]. Assuming that the mobile terminals have an associated mean velocity v and uniformly populated with a density ρ over a location area having a boundary length of L, then the rate of flow of mobile users, R, out of the region is given by

$$R = \frac{\rho \, vL}{\pi} \quad (1)$$

This model is simple to analyse and provides good results when the population is very large since it takes into account both average population density and velocity for the location area under consideration. However it cannot be applied to small populations and so it is difficult to apply this model when individual movement patterns are desired

2.2 Gravity Model

This model has been used extensively in the area of transportation research to model human movement behaviour. The amount of traffic T_{ij} moving from region i to region j is described by

$$T_{ij} = K_{ij} P_i P_j \quad (2)$$

where P_i is the population in the region i, and $\{K_{ij}\}$ are parameters that have to be determined for all possible region pairs (i, j). Gravity models characterise aggregate population movement on a wide area scale and have been used to model *national* and *international* population movement [7]. The advantage of this model is that frequently visited locations can be easily modelled since they are regions of high attractivity. However, as well as being limited to large populations, the major disadvantage of this model is that it requires a lot of input parameters such as demographic and cartographic data. This was one of the main objections to using this approach directly.

2.3 Markovian Model

The Markov model [6] Characterises individual user's movement between cells.Movement from one cell to an adjacent cell is defined according to a transitional probability distribution. This model has been used for performance analysis of selective location areas (LA) and threshold- based update schemes. One of the limitations of this approach is that there is no concept of movement history or trip of a particular mobile user such as frequently used routes between non-adjacent regions.

3. MODELLING APPROACH

Our mobility model extracts some of the main features of the above models. We use the gravity model in a special form to determine the number of mobiles present at a specific location based on the attractivity of that location and population movement is characterised by a fluid model.

Our modelling approach takes into account factors related to *class of mobility*, *area zones*, *attractivity points* and *time periods* which originate from transport theory [2]. These factors are detailed below:

- **Classes of Mobility –** mobile users having the same mobility behaviour are grouped into a specific class of mobility (CM). The corresponding CM also reflects mobile users' calling behaviour and use of services. For our model, three CM have been considered: *Business*, *Residential* and *Others*.
- **Area Zones** – the geographical area under consideration is divided into regions having specific mobility related characteristics. Four environments have been considered: *Working*, *Domestic*, *Shopping* and *Streets.*
- **Attractivity Points** (APs) – Represent locations that attract users with a specific CM and at which mobiles spend a certain amount of time. The attractivity of an AP is a function of time and varies for each CM based on the environment of the mobile. For instance, office premises would attract a large flow of MUs during morning hours and outflow of MUs during evening hours. Each CM 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 zone's attractivity during a specific time of the day.
- **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) characterising the movement of MUs from/to the city centre 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 MUs of a particular CM reside at certain APs (e.g. work places) and finally the *off peak hour* indicating minimum usage of the wireless network by MUs.

These four factors are expressed in the mobility model by introducing the concept of *poles of gravity* (PGs).

PG is a geographical location that contains a mass of MUs. Each PG has an associated decription defining describing the population density of MUs for each CM with respect to the location's attractivity and time. This means that PGs characterise the population movement based on the factors detailed in our modelling approach and this notion introduces a discretisation of mobile users in space and time. The population densities of specific class of mobility vary from PG to PG so, for example, the density of mobile users in the Business Class is expected to be denser in a working environment PG and sparse in residential area PGs' during the busy hour. Together with the time-dependent attractivity function, the PG concept conceptualises a stochastic system to describe mobile subscriber movement in a predefined topology of the wireless network.

4. SYSTEM MODEL

The system model extracts some of the properties of the fluid, gravity and Markovian models and has been divided into three sub- models: *Physical Sub-Model*, *Gravity Sub- Model* and *Fluid Sub-Model* as shown in Figure 1.

The physical sub- model specifies logical connectivities among the PGs in the geographical topology under consideration while the gravity sub- model constantly calculates the *attractivity* of PGs in the system and determines the time spent by each mobile in a PG. The fluid sub-model fixes the law of circulation of each mobile unit between the poles taking into consideration the *attractivity* defined by the gravity law and *distance of separation* determined by the physical sub-model. These sub-models are inter-dependent and connected as shown in Figure 1 through the coefficients of *elasticity*, *entropy* and *viscosity*.

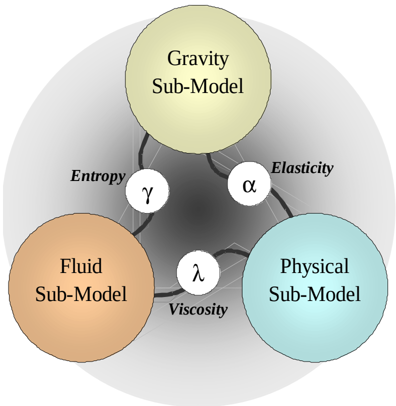


Figure 1: System Model

The coefficient of elasticity is defined as the model's reactivity to restore equilibrium when a change in attraction occurs among the PGs. Entropy is a measure of introducing a degree of friction between two different PGs when a change of attraction occurs. The coefficient of viscosity gives a perception of distance between two zones of the originating mobile to its destination. While the coefficient of elasticity governs the stability of the model, the coefficients of entropy and viscosity dictate the most probable path of mobile in the given topology under investigation.

4.1 General Notation & Definitions

The input parameters to the model are detailed below:

T	Duration of simulation, based on a 24-hour day
M	Total number of mobile users in the geographical area under consideration
R	Angular connectivity
α	Coefficient of elasticity and $\alpha \in [0\ 1]$
γ	Coefficient of entropy and $\gamma \in [0\ 1]$
β	Coefficient of viscosity and $\beta \in [0\ 1]$
A_j	Mean Sojourn Time in PG_j
S_j	Surface area over which mobile users of any CM is distributed in the PG_j
$D_{j,K}($	Initial concentration of mobile users for CM_K, where K $\in$ (Business, Leisure, Shopping, Residential) for PG_j
$Att_{j,K}(t)$	Attractivity of CM_K for PG_j during simulation time t and is $\in [0\ 1]$
$l_{K,j}(t)$	Current number of mobiles in CM_K at PG_j at time t

4.2 Physical Sub-Model

The physical sub-model defines (1) the geographical positioning of PGs based on attraction points and population movement, (2) the spatial distribution of mobile units at those points specified by S_j and (3) the logical connectivities among the PGs representing possible movement direction through the angular connectivity *R*. An illustration of the physical sub-model is shown in Figure 4. for the area of Bristol where the city is overlaid with PGs based on the geographical and demographic characteristics of the area. PGs are dense in the city centre and along the roads while they are sparse in rural areas.

Each PG is divided into *R* equal sectors and the minimum distance criterion is used for interconnecting PGs is initiated. This together represents the most probable paths undertaken by mobile users movement. The mobile users are uniformly distributed over the PG given by Equation 3:

$$z = r e^{i\theta} \tag{3}$$

where r = $\left[0, \sqrt{\frac{S}{\pi}}\right]$ and $\theta = [0, 2\pi]$ (θ is uniformly distributed over [0, 2π]).

4.3 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 people present at a specific location is dependent on the attractivity of the location.

This sub-model extracts some properties of gravity models and the similarities can be easily seen in the *gravity law* which dictates the temporal behaviour of mobiles and stability of the mobility model as detailed below.

4.3.1 Gravity Law

The 'Gravity Law' constantly calculates the steady state value of mobiles, $C_{j,K}(t)$, for each of the classes of mobility present in all the PGs when a change in attractivity occurs. Each CM can be considered as a waiting queue having infinite capacity whose steady state value is expressed as:

$$C_{j,K}(t) = M \times P_{aj,K}(t) \tag{4}$$

where M is the total number of mobiles considered during simulation and $P_{aj,K}(t)$ is the *probability of attractivity'*, given by Equation 5:

$$P_{aj,K}(t) = \frac{D_{\mathrm{j,K}}(0) \times Att_{j,K}(t) \times S_j}{\sum_{j=1}^{N} \sum_{K=1}^{O} D_{\mathrm{j,K}}(0) \times Att_{j,K}(t) \times S_j} \tag{5}$$

where N is the number of PGs in the topology under consideration and O is the number of mobility classes, at PG_j.

The departure process of MUs from one PG to another is determined by the inter-departure time. 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 transition probability matrix governed by the *'fluid law'*. The gravity sub-model is an enhancement of the HLPPS algorithm and as such, the fraction of time spent by a MU in a specific PG is proportional to the actual number of mobiles in its corresponding CM. This process has the underlying property of the *Markov* process expressed by Equation 6:

$$ID_{K,j}(t) = A_j \alpha_j^{\phi_{K,j}(t)} \tag{6}$$

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

$$\phi_{K,j}(t) = \frac{l_{K,j}(t) - 1}{C_{K,j}(t)} \tag{7}$$

Initially, $C_{K,j}(t)$, and the current number of mobiles, $l_{K,j}(t)$, are assumed to be equal (where $C_{K,j}(t)$ >> 1) such that $\phi_{K,j}(t) \approx 1$. This state in the model is referred to as the steady state of the system and to characterise stability, a similar approach based on the *positive Harris recurrent* terminology detailed in [12] and [13] has been used. This concept is best illustrated below:

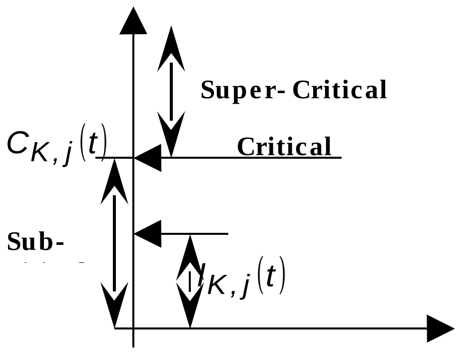


Figure 2: General representation of stability conditions for a CM_K at PG_j

Referring to Equation 6, for a particular CM, K, PG_j, three states can be identified as defined below:

1. $ID_{K,j}(t)$ *decreases from* A_j *to* $A_j \alpha_j$, $0 < l_{K,j}(t) < C_{K,j}(0) \Rightarrow 0 < \phi_{K,j}(t) < 1$
2. $ID_{K,j}(t) = A_j \alpha_j$: $l_{K,j}(t) = C_{K,j}(0)$, $\Rightarrow \phi_{K,j}(t) = 1$
3. $ID_{K,j}(t)$ *decreases from* $A_j \alpha_j$ *to* 0, $l_{K,j}(t) > C_{K,j}(0) \Rightarrow \phi_{K,j}(t) > 1$

Referring to the analogy in [12], conditions **1**, **2** and **3** can be referred to as strictly *sub-critical* while condition **4** is referred to as *critical* and condition **5** described as *super-critica*l.

4.4 Fluid Sub-Model

Fluid models are continuous and conceptualise individual movement behaviour as movement mass rather than individual movement patterns [14] on a macroscopic level. Our movement model exploits the features of the fluid model to characterise mobile user displacement at a microscopic level characterised by the *Brownian Movement Model* through a diffusion process. Individual MU movement is initiated at the end of its inter-departure time which can result in a change in the MU's current location and class of mobility independent of its class history This is characterised through the *transitional probability matrix* defined by the *fluid law*.

4.4.1 Fluid Law

The fluid law fixes the law of circulation down to the level of individual mobiles between the poles defined by physical sub-model through the transitional probability matrix. This matrix defines the probabilities of a mobile user in a class of mobility, CM_K, leaving its present position in a source pole, PG_i, to a destined PG_j and has the following properties:

- Inversely proportional to the excess population intensities, Δ_{ij}, of PG_i and PG_j
- Directly proportional to the distance of separation, $d_{\min ij}$, between i PG and j PG

The above properties are defined through the transitional probability matrix defined by Equation 8:

$$P_{KL}(t) = \gamma \quad {}^{-th(\Delta} \tag{8}$$

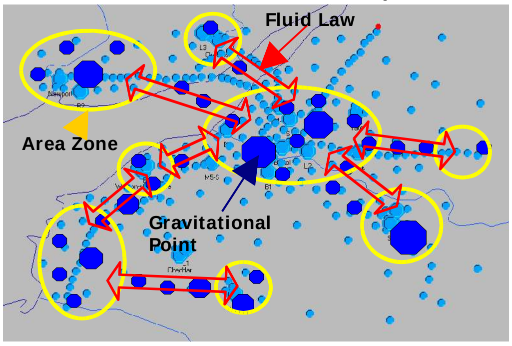
where $\Delta_{ij} = \phi_{K,i}(t) - \phi_{K,j}(t)$. The speed of a mobile is given by:

$$V_s(t) = V_f\left(1 - \frac{X_{jam}}{X_i(t)}\right) \tag{9}$$

where $X_i(t)$ is the distance between MUs in the PG i at time t and V_f is the free flow speed which is 60 km/h.

5. MOBILITY SIMULATOR

The mobility model has been validated by simulation. The architecture of the simulator is shown in Figure 3. It is a discrete event handler driven by the HLPPS



queue model.

At the initialisation of the simulation, the PG are placed over the region of investigation according to the physical sub-model and the initial concentration for each CM, $D_{j,K}(0)$, and the initial attraction for the CM is defined through the attractivity function $Att_{j,K}(t)$. The number of mobiles in each CM is calculated through the gravity law based on the attractivity and the surface over which the mobiles are distributed. The simulator interconnects each PG based on the minimum distance criteria via the angular connectivity and specifies the most probable path that mobiles will take during simulation determined through the fluid law. Each event is enqueued at an instant in the future determined through its corresponding inter-departure time, and triggers the mobile to move.

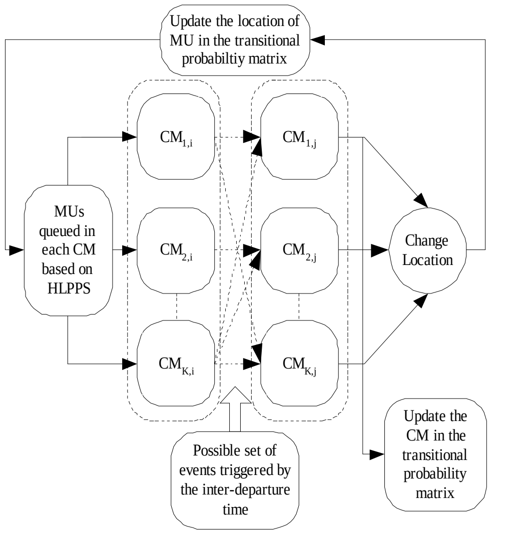


Figure 3: Mobility Simulator Architecture

The mobility simulator allows the tracking of mobile users on a per mobile basis. The statistics generated relate to each mobile's ID, its previous and present CM as well as its previous and present *x* and *y* location co-ordinates in Km. These statistics are collected in an output file at the end of simulation and are used as the input simulation file in the modelling of teletraffic related issues.

5.1 Simulation: Mobility Model Validation

Using the modelling approach detailed in section 3 and the simulator described above, user movement has been modelled for the city area of Bristol, UK shown in Figure 4. The depicted region has an extension of 5Km × 5Km and shows the positioning of PGs in four different environments considered *Working*, *Residential*, *Shopping* and *Streets*.

Figure 4: Interaction of Physical, Gravity and Fluid Sub Models showing the geographical locations of PG in the Area of Bristol *(Note: I need to update this picture)*

The simulation time ranges from 7.00 a.m. to 10.00 a.m., thus including mobile user displacement before, during and after morning rush hours (7.00 a.m. – 9.00 a.m.).

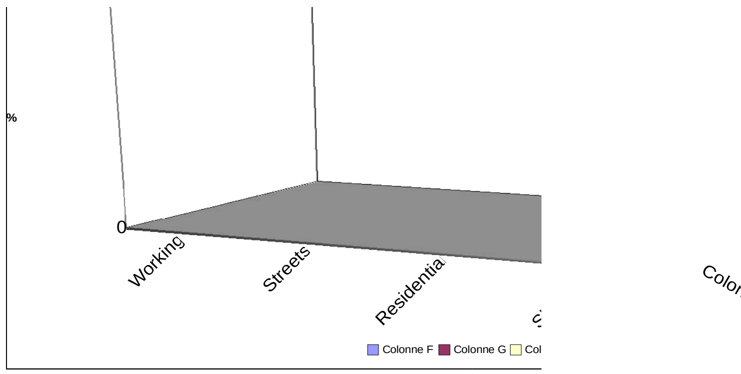


Figure 5 (a): Spatial Distribution of mobiles at 7.00 a.m.

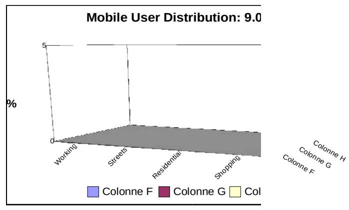


Figure 5 (b): Spatial Distribution of mobiles at 9.00 a.m.

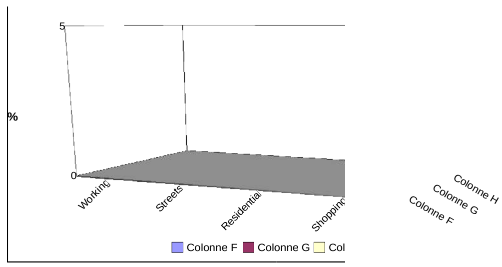


Figure 5 (c): Spatial Distribution of mobiles at 10.00 a.m.

Figure 6 (a), (b) and (c) illustrates the working of the model based on population movement in the different environments with time.
More explanation????
6.
Add section for conclusions and future work

6. MAPPING TERMINAL MOBILITY INTO TRAFFIC DEMAND

7. CONCLUSION

In this paper, we have introduced a mobility model which allows the tracking and location of mobile users on a per mobile basis. The model is based on queueing theory and we have used the results of Head-of-the Line Proportional Processor Sharing algorithm to model user displacement in the geographical region of Bristol. We have also introduced the concept of pole of gravity which unables us to define user movement at different granularity in space. As a first step, for further investigation related to teletraffic issues in the context of a wireless network, we have also provided a mapping between user displacement into traffic demand.

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