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ON THE ACCURACY OF MOBILITY MODELLING IN WIRELESS NETWORKS

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Abstract

In a wireless mobile network, two major problems arise: poor performance of the wireless layer and effect of user mobility. The problems related to limited available radio bandwidth and radio channel errors seem to be solved by CDMA technique applied in 3G mobile systems. The bandwidth that is provided by CDMA air interface is enough for present mobile multimedia applications. However such applications are sensitive to the degradation of QoS parameters. Graceful degradation could happen when too many mobiles arrive to the same radio cell. To avoid such situations the Call Admission Control (CAC) has to limit the number of newly accepted connections. Terminal mobility causes problems in call admission control because the number of active mobile terminals in a cell is a random variable. In this paper we introduce a new method to predict the number of terminals in each cell. Based on this information a more effective CAC algorithm can be applied in order to ensure user's satisfaction.

Keywords: mobility modelling, call admission control.

1. Introduction

Due to the development in radio techniques more bandwidth is available for mobile users. GPRS and UMTS packet switched radio access networks enable IP-based multimedia traffic connections (such as voice calls, video conferencing, multimedia SMS, etc.). Besides bandwidth, the user's satisfaction is also a very important issue. In order to satisfy end-to-end QoS requirements of multimedia connections, resource reservations on air interface and in the backbone network have to be made at different points of the 3G networks. To enable efficient radio resource reservation, it is an important task to examine the user's movement and call characteristic behaviour, in order to estimate the future resource demands. Hence we give a short survey on the role of mobility models in wireless mobile networks:

- Every radio cell boundary or administrative domain crossing implies several administrative messages. These messages are consuming precious wireless bandwidth. Based on the prediction of the most possible future user movements, handover arrangements can be made in advance. This means smaller interruption to user traffic flow and improves QoS support.

- The future number of terminals in radio cells together with the estimation of future bandwidth demand of mobile terminals enables operators to employ resource reservation based, foreseeing CAC algorithms to provide better QoS support.
- The application of an optimal location update and delay constrained paging strategy is also a very important problem. The paging delay has to be minimised, so the paging area has to be small. But on the other hand the rate of location update messages has to be infrequent in order to minimise the wasting of bandwidth and battery life.

All the above mentioned problems have one common aspect: the optimal solution can only be found, if the future number and bandwidth demand of mobile terminals can be predicted precisely for each radio cell. In the literature several mobility models can be found, but the suitability (e.g. what cell-parameters should be measured in a real network, in order to determine the mobility model's parameters and how to carry out this process) and accuracy of these models are not examined. In this paper we introduce a new Markov mobility model, especially appropriate for accurate prediction of the future number of mobile users in an urban environment. The other advantage of our model is its simplicity, making it useful for numerical analysis. The accuracy of the new mobility model is compared to the random walk model. The resulting equations can be utilised in enhanced CAC algorithms.

This paper is organised as follows: in section two we describe mobility models found in the literature, in section three we introduce our new Markov model. The future number of mobile terminals for a radio cell is calculated in section four. The accuracy of mobility modelling techniques is investigated by simulation in section five, and section six concludes the paper.

2. Mobility Models

In the literature several mobility models can be found, which describe aggregate or individual movement behaviour [1].

The *Fluid Flow* model characterises aggregate movement behaviour as the flow of a fluid. Mobile users are assumed to move at an average velocity of v, and their direction of movement is uniformly distributed over $[0, 2\pi]$. This model is accurate for estimating boundary-crossing rate in a symmetric grid of streets (i.e., Manhattan-style). This model has been used to study the profile-based update scheme. One of the limitations of this model is that it describes aggregate traffic and is difficult to apply to scenarios where individual movement patterns are desired.

The *Gravity model* has been used extensively in the area of transportation research to model aggregate human movement behaviour.

The *Time-varying Gaussian User Location Distribution* arises as a result of isotropic random user motion with drift, defined as the mean velocity in a given direction; it can be used to model directed traffic such as vehicles along a highway.

As most of the users are likely to be pedestrians in a *PCN*, we have chosen the random walk and the Markovian mobility models, because these are most appropriate for modelling pedestrian movement. We assume that the service area is covered by hexagonal radio cells of the same size. We also assume that the movements of the users are stochastic and independent of one user to another. The time is divided into time slots, and users moving even at maximum speed can cross only at most one cell boundary during a timeslot.

The *Discrete Time Random Walk* model [2] is the most commonly used mobility model to describe individual movement behaviour. In this model the direction of a user is identically distributed between 0 and 2π. The user's speed is between 0 and *Vmax*. After moving in a direction with a randomly chosen speed for a given Δt time, the user changes its direction and speed.

In the One Dimensional Markovian Movement model during each time slot a user can be in three different states [3]:

- The stationary state (S)
- The right-move state (R)
- The left-move state (L)

The user is assumed to be in cell i at the beginning of a slot. If the user is in state S during a slot, then it remains in cell i, if the user is in state R, it moves to cell $(i+1)$, and if it is in state L, then it moves to cell $(i-1)$.

Let us define $X(t)$ random variable. $X(t)$ represents the movement state of a given terminal during time slot t. We assume that $\{X(t),\ t = 0, 1, 2, \ldots\}$ is a Markov chain with transition probabilities [3]:

$$p_{k,l} = \text{Prob}\,[X(t+1) = l / X(t) = k],$$

as follows:

$$p_{R,R} = p_{L,L} = q, \quad p_{L,R} = p_{R,L} = v,$$
$$p_{S,R} = p_{S,L} = p, \quad p_{L,S} = p_{R,S} = 1 - q - v, \quad p_{S,S} = 1 - 2p.$$

The Markov chain concerned can be seen in *Fig. 1*.

For example $p_{S,R} = p_{S,L} = p$ transition probability means that if the user is in state S it will change to state R or L in the next slot with probability p.

3. The Extended Markov Model for Modelling Two-Dimensional Movement

Two-dimensional Markov models can be found in the literature. In [5] by defining six states for the six adjacent cell's directions, a two-dimensional Markov model is applied, but it has the drawback that it is too complex and one cannot give a closed form for the steady-state probabilities.

Our goal is to define a simple yet appropriate model, therefore we extended the one-dimensional model to a two-dimensional model retaining its simplicity, by limiting the possible states of the mobile user. The main idea of our model is

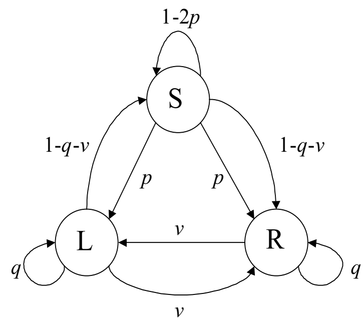

Fig. 1. State diagram of the one-dimensional Markov chain

to separate the neighbouring cells into two groups according to the typical user movement's direction. In *Fig. 3* the scheme is applied to a cluster of hexagonal radio cells, assuming a typical horizontal movement direction.

In this model we do not presume anything about the user's vertical movement, we are limited to its horizontal movement (or the contrary). Usually, real-life movements have only one major direction (on the street, or in a corridor), thus our model is capable of simulating these types of movements (*Fig. 2*).

We assume that a user is in cell i at the beginning of a slot. If the user is in state S during a time slot, it remains in cell, like the one-dimensional model. If the user is in state R, it moves to one of the cells that are on the right-hand side of the dividing line. The three destinations have equal probabilities. In the same way, if the user is in state L, it moves to one of the cells, which are on the left-hand side of the dividing line. In this case the user also can be in three states and the Markov chain and the transition probabilities do not change at all.

Our goal is to calculate the steady-state probabilities P_S, P_R and P_L in the Markov chain, by p, q and v probabilities. These probabilities can be determined by measured network parameters (a detailed explanation will follow in Section 4). These parameters are time-dependent and different for each cell.

The balance equations for the Markov chain are given as:

$$2 \cdot P_S \cdot p = P_R \cdot (1 - q - v) + P_L(1 - g - v) \tag{1}$$

$$P_L \cdot (1 - q) = P_S \cdot p + P_R \cdot v \tag{2}$$

$$P_R \cdot (1 - q) = P_S \cdot p + P_L \cdot v \tag{3}$$

We also know that $P_S + P_L + P_R = 1$, thus the steady-state probabilities of the Markov chain can be calculated:

$$P_S = \frac{1 - q - v}{1 - q - v + 2 \cdot p} \tag{4}$$

$$P_L = P_R = \frac{p}{1 - q - v + 2p} \tag{5}$$

We also have to mention that when the movement has a typical direction, then the state diagram of the Markov walk is different from *Fig. 1*. Therefore we have extended our model, as shown in *Fig. 3*. The modified model is more appropriate for real life scenarios.

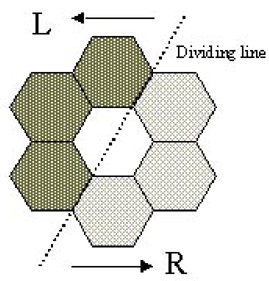

Fig. 2. The two directions in the two-dimensional model

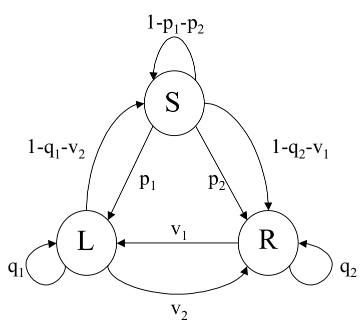

Fig. 3. The state diagram of the Markov walk with different directions

In this case the left-move state and the right-move state have different probabilities, because the transition probabilities are not symmetric.

The balance equations for the Markov chain are then given as:

$$P_S \cdot (p_1 + p_2) = P_L \cdot (1 - q_1 - v_2) + P_R \cdot (1 - q_2 - v_1), \quad (6)$$
$$P_L \cdot (1 - q_1) = P_S \cdot p_1 + P_R \cdot v_1, \quad (7)$$
$$P_R \cdot (1 - q_2) = P_S \cdot p_2 + P_L \cdot v_2. \quad (8)$$

Just like to the one-dimensional case, we can calculate the steady-state probabilities of the transition probabilities. The result can be seen in *Eqs.* (9), (10) and (11):

$$P_S = \frac{1}{(1 + \frac{v_1 \cdot (p_1 + p_2) + p_1 \cdot (1 - q_2 - v_1)}{v_1 \cdot (1 - q_1 - v_2) + (1 - q_1) \cdot (1 - q_2 - v_1)} + \frac{1}{\frac{v_2 \cdot (p_1 + p_2) + p_2 \cdot (1 - q_1 - v_2)}{v_2 \cdot (1 - q_2 - v_1) + (1 - q_2) \cdot (1 - q_1 - v_2)}}} \tag{9}$$

$$P_L = P_S \cdot \frac{v_1 \cdot (p_1 + p_2) + p_1 \cdot (1 - q_2 - v_1)}{v_1 \cdot (1 - q_1 - v_2) + (1 - q_1) \cdot (1 - q_2 - v_1)} \tag{10}$$

$$P_R = P_S \cdot \frac{v_2 \cdot (p_1 + p_2) + p_2 \cdot (1 - q_1 - v_2)}{v_2 \cdot (1 - q_2 - v_1) + (1 - q_2) \cdot (1 - q_1 - v_2)} \tag{11}$$

4. Future User Location Calculations

Our task is to predict the number of mobile terminals for time slot t_{i+1} for each radio cell in the PCN, based on the data collected during timeslot t_i. Once the future position of mobile terminals is determined, one must calculate the bandwidth demand of these mobile terminals (which is not in the scope of this paper) based on the traffic models that can be found in the literature. In a packet switched mobile radio network the most commonly used multimedia connections are the Web-browsing, video-conferencing and voice calls. In [6] a detailed model can be found to model Web traffic. For modelling voice connections, exponentially distributed call-holding time is used widely in the literature. According to these models, the future bandwidth demand of mobile terminals can be predicted. Following the estimation of future user position and bandwidth demand, a foreseeing resource reservation based CAC algorithm [7] can be carried out.

In this section we calculate the future number of mobile terminals relying on the random walk model and our modified Markov mobility model.

4.1. One-Ring and Two-Ring Based Predictions Relying on the Symmetric and Handover Vector Random Walk Models

We are introducing some modifications in the random walk model, in order to simplify the calculations in cellular systems. The user's moving directions are limited only to the six neighbouring cells. At discrete Δt time intervals, a mobile user can make a move to one of the neighbouring cells with probability q, or stay in the current cell with probability $(1 - q)$. When the mobile user leaves a cell, there is an equal ($p = 1/6$) probability that he will move to a given neighbouring cell. A user can move only from the centre of radio cell to the centre of a neighbouring cell.

The maximum distance the user can cover during a Δt discrete time interval is the distance between the centres of two adjacent cells. This conception simplifies the analysis, while it requires the measurement of only one network parameter: mobility q. The limitation of this approach is that the typical direction of the mobile user's movement is not taken into account.

If the probabilities of the six directions are different (e.g. during morning rush hours most of the users are moving towards office buildings) we can define handover vector **h** for each cell. This vector consists of six elements and is constructed based on measuring the cell boundary crossings. Each element of the handover vector is the probability of one direction. Let $\overline{h}_k[i]$ mean the probability that a user will move from cell k to an adjacent cell i. By adding this extension to the model, the model becomes more complex, but it can better approximate the characteristics of realistic user movements.

In order to calculate the future number of mobile terminals in cell k, we use the concept of a ring, as shown in *Fig. 4*. The ring consists of cells surrounding cell k. If we select cell k (as indicated) as the centre, cells labelled '1' form the first ring around cell k. Cells labelled '2' form the second ring around cell k, and so on. We use this concept to simplify the calculations, because we are only interested in the number of users arriving to or leaving a given ring during a time period, internal movements (inside the rings) are unconcerned. Our goal is to predict the number of users in cell k in time slot t_{i+1} and t_{i+2}, based on the number of users in cell k, the first ring and the second ring at time slot t_i.

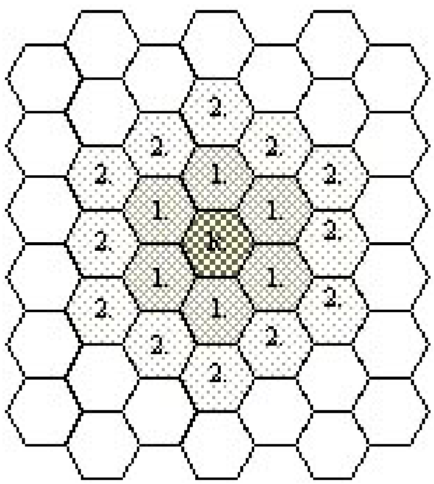

Fig. 4. Ring-based random walk model

First we investigate the symmetric random walk model. In this case, there is only one model parameter; q, which is the probability of a user leaving its current cell.

Our goal is to calculate $N_0(t+1)$ and $N_0(t+2)$ if we know $N_0(t)$, $N_1(t)$ and

$N_2(t)$. Where $N_i(t)$ is the number of mobile users in ring i of time slot t. If the terminal is in one of the cells in ring i, the probabilities that a movement will result in an increase $(p+(i))$ or decrease $(p-(i))$ of the distance from the central cell are [2].

$$p+(i) = \frac{1}{3} + \frac{1}{6 \cdot i} \tag{12}$$

$$p-(i) = \frac{1}{3} - \frac{1}{6 \cdot i} \tag{13}$$

For example, if a user is in ring 1, then $p+(i) = 1/2$ and $p-(i) = 1/6$. Based on these results we can give the number of users in cell 0 during time $(t+1)$ and $(t+2)$:

$$N_0(t+1) = N_0(t) \cdot (1-q) + N_1(t) \cdot \frac{1}{6}q \tag{14}$$

$$N_0(t+2) = N_0(t) \cdot \left[\frac{1}{6}q^2 + (1-q)^2\right] + N_1(t) \cdot \left[\frac{1}{3} \cdot q \cdot (1-q)\right] + N_2(t) \cdot \frac{1}{24}q^2. \tag{15}$$

The symmetric random walk model can be further extended by applying the handover vector. The handover vector describes the probabilities of a mobile node moving to one of the six neighbours of the cell. In this case, the results will be more complicated than *Eqs.* (14), (15), because the number of users has to be weighted by the respective elements of the handover vector.

First let us examine the one-ring case. A column and row number identify every cell: i and j (see *Fig. 5*).

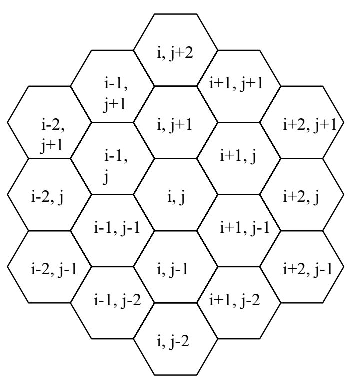

Fig. 5. Cell numbering

The future number of mobile terminals has to be calculated for cell (i, j), so we will give an equation to predict $N_{i,j}(t+1)$ assuming that the number of nodes in adjacent cells is known for the time period t.

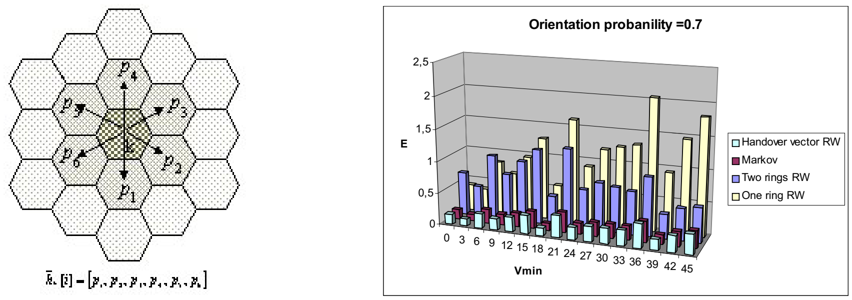

Fig. 6. The directions of the elements of the handover vector

The elements of the handover vector are representing the user's movement probabilities into the six neighbouring cell directions, as it can be seen in *Fig. 6*. The index of the vector indicates the corresponding cell.

The future number of users in time slot $t+1$ consists of two parts: mobile nodes were in the given cell in time slot t and a $(1-q)$ part of them will stay in the same cell. The other part is the users arriving from adjacent cells, weighted by the corresponding elements of the handover vector. The equation concerning these two parts is (16).

$$\begin{aligned} N_{i,j}(t+1) = {} & N_{i,j}(t) \cdot (1-q) + q \cdot (h_{i,j+1}[1] \cdot N_{i,j-1}(t) \\ & + h_{i+1,j}[6] \cdot N_{i-1,j}(t) + h_{i+1,j-1}[5] \cdot N_{i+1,j-1}(t) \\ & + h_{i,j-1}[4] \cdot N_{i,j-1}(t) + h_{i-1,j-1}[3] \cdot N_{i-1,j-1}(t) \\ & + h_{i-1,j}[2] \cdot N_{i-1,j}(t)). \end{aligned} \tag{16}$$

To perform the one-ring prediction with (16), only the actual number of users in the neighbouring cells and the handover vector values need to be known.

The two-ring prediction is executed in two steps. First the number of users in time slot $t+1$ has to be calculated for the centre cell, and separately for the cells in the first ring according to (16). The next step is to calculate *Eq.* (16) for time slot $t+2$ (17).

$$\begin{aligned} N_{i,j}(t+2) = {} & N_{i,j}(t+1) \cdot (1-q) + q \cdot (h_{i,j+1}[1] \cdot N_{i,j-1}(t+1) \\ & + h_{i+1,j}[6] \cdot N_{i-1,j}(t+1) + h_{i+1,j-1}[5] \cdot N_{i+1,j-1}(t+1) \\ & + h_{i,j-1}[4] \cdot N_{i,j-1}(t+1) + h_{i-1,j-1}[3] \cdot N_{i-1,j-1}(t+1) \\ & + h_{i-1,j}[2] \cdot N_{i-1,j}(t+1)). \end{aligned} \tag{17}$$

In (17) a constant q parameter is presumed for every cell, although in a real scenario this assumption will fail. For this reason it is advisable to let q be different for every cell in the network. The modified equation is the following:

$$
\begin{aligned}
N_{i,j}(t+2) = N_{i,j}(t+1) \cdot (1 - q_{i,j}) \\
&+ q_{i,j+1} \cdot h_{i,j+1}[1] \cdot N_{i,j-1}(t+1) \\
&+ q_{i+1,j} \cdot h_{i+1,j}[6] \cdot N_{i-1,j}(t+1) \\
&+ q_{i+1,j-1} \cdot h_{i+1,j-1}[5] \cdot N_{i+1,j-1}(t+1) \\
&+ q_{i,j-1} \cdot h_{i,j-1}[4] \cdot N_{i,j-1}(t+1) \\
&+ q_{i-1,j-1} \cdot h_{i-1,j-1}[3] \cdot N_{i-1,j-1}(t+1) \\
&+ q_{i-1,j} \cdot h_{i-1,j}[2] \cdot N_{i-1,j}(t+1)).
\end{aligned}
\tag{18}
$$

As a result, we have managed to find a closed formula to predict the future number of users in both cases (one and two rings). The model parameters are different for every cell, just like in a real life situation.

4.2. One-Ring Based Predictions Relying on our Extended Markovian Model

We gave a closed form of the steady-state probabilities of the Markov model (P_S, P_R, P_L) in Section 3. With these probabilities we can calculate $N_0(t+1)$ if we know the number of users in the neighbouring cell at time t, but of course we have to distinguish the left-hand side cells from the right-hand side cells (*Fig. 3*).

$$
N_0(t+1) = N_0(t) \cdot P_S(0) + \frac{1}{3} \cdot \sum_{l=1}^{3} N_l(t) \cdot P_R(l) + \frac{1}{3} \cdot \sum_{r=1}^{3} N_{r(t)} \cdot P_L(r) \tag{19}
$$

In *Eq.* (16) the steady-state probabilities are different for each cell, and time-dependent in a real network. In the Markov model there is more than one system parameter. Thus the equations are more complicated but they can better approximate the real movements. We introduced two two-dimensional Markov models in Section 2. In the first one P_R and P_L were equal, thus we had three transition probabilities: p, q and v. In the second one P_R and P_L could be different, thus we had six transition probabilities p_1, p_2, q_1, q_2, v_1 and v_2. These transition probabilities can be determined by measurements; the cell has to register the number of users arriving at the cell from different directions. The number of users leaving the cell toward a given direction is also to be recorded. By exchanging these values between adjacent cells (by means of signalling messages), the transition probabilities can be calculated for each cell in the network. The measurement-based determination of the model's parameters results in flexibility. This is the main advantage of this model, because it adaptively adjusts itself to the time-varying user movement characteristics.

5. Simulation Results

The accuracy of the mobility models is investigated by means of simulations. The test scenario consists of 49 hexagonal shaped radio cells. There were 300 mobile terminals in the network; every simulation loop was running for 1000 simulation time slots. We have investigated two situations: first the users were moving randomly and independently of each other according to the random walk model (the first version of the simulator), and (enhanced version). At the beginning of the simulation the users were uniformly distributed over the simulation area. Every user moved from the centre of a cell to the centre of a cell. When a mobile user reaches a cell centre, then it picks a random speed between $V_{\min}$ and $V_{\max}$ and a random direction. The maximum speed of the users in the simulation (*Vmax*) was limited, in order to prohibit multiple cell boundary crossings during one time slot:

$$V_{\max} = \frac{\sqrt{3} \cdot R}{\Delta t}, \tag{20}$$

where R is the radius of a hexagonal cell and Δt is the simulation time slot. In our simulation we have compared the accuracy of the prediction of our mobility models. Let E denote the error of the prediction.

$$E = \frac{|(\text{Actual number of users in the cell}) - (\text{Predicted number})|}{(\text{Actual number of users in a given cell})}.$$

Orientation probability represents the drift in the movement of the users, e.g. when the orientation probability is high, most of the users are moving in the same direction.

First we examined the prediction error (E) in function of the user mobility (q). The orientation probability was set to a constant rate of 0.7. By limiting the minimum user speed, $V_{\min}$, the user's mobility increases.

As it can be seen in *Fig. 7* our modified Markovian model provides the most precise prediction and the performance of the one-ring random walk model deteriorates when the user mobility increases. The explanation of the increasing error rate is that – in contrast to the two-ring prediction – it does not take the remote users with higher speeds into account.

In the next scenario the users mobility was low (V_{min} is set to zero). In this case, the role of orientation probability was investigated, in the case of all the four predictions. As it can be seen in *Fig. 8*, the order of the models is: Markovian, handover vector random walk, one-ring random walk and two-ring random walk. It is important to point out, that all the predictions – as expected – achieved lower error levels, due to lower terminal mobility. The orientation probability doesn't have a significant influence on the performance of the predictions at low mobility levels (*Fig. 8*).

The reason for the bigger error rate of the two-ring random walk models is the bigger uncertainty of the more remote prediction (unlike mobiles with high mobility, slowly moving users do not affect cells from vide ranges ($r = 2D$)).

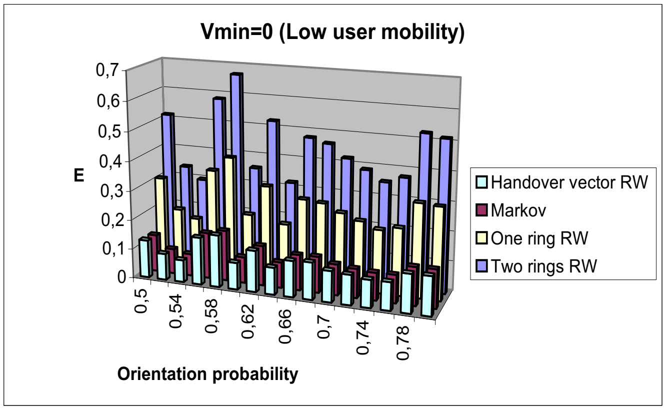

Fig. 7. Prediction error versus user mobility

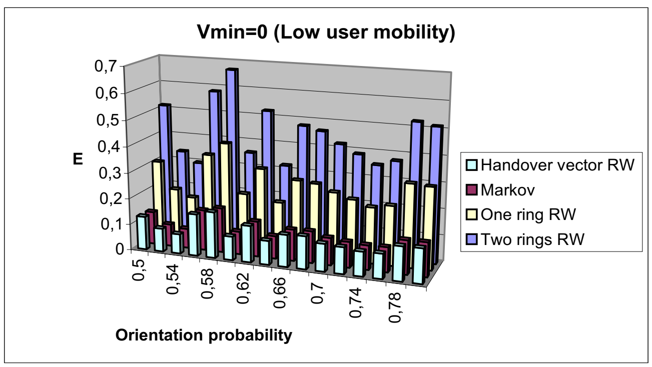

Fig. 8. Prediction error versus orientation probability

By increasing the mobility level ($V_{\min}$ is set to 40) an interesting observation can be made. The Markovian model and the handover vector model are still the best, but the two-ring random walk outperforms the one-ring random walk. The explanation for this phenomenon is that the two-ring approach also takes the influence of remote but fast moving users into consideration (*Fig. 9*).

During the second simulation run, user's mobility was simulated according to a Gauss-Markov model, which resembles real-life user movement characteristics. (We are still working on our original goal, namely to study real-life movement data, gathered from a mobile service provider). The users moving speed and direction depend on the past speed and direction. In the simulation, 1500 users were initialised (with a random speed between $V_{\min}$ and $V_{\max}$, random direction between 0 and 2π) and uniformly distributed and the simulation time was 3000 time slots.

The Gauss–Markov Mobility Model was originally proposed for the simula-

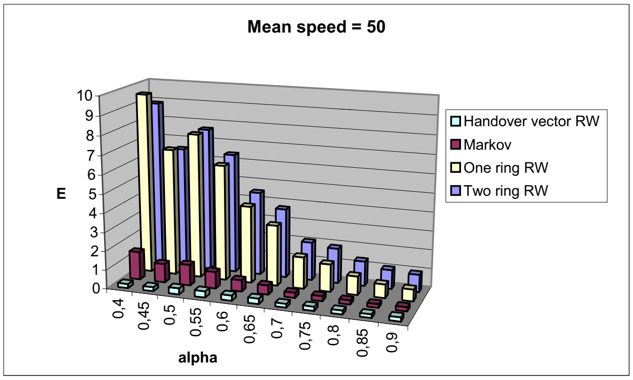

Fig. 9. Prediction error versus orientation probability

tion of a PCS, and it was designed to adapt to different levels of randomness by one tuning parameter.

Initially each MN is assigned to a current speed and direction. At fixed intervals of time (n) movement occurs by updating the speed and direction of each mobile terminal. Specifically, the value of speed and direction at the n^{th} instance depends on the value of speed and direction at the $(n-1)^{\text{st}}$ instance and a random variable:

$$\begin{aligned} s_n &= \alpha \cdot s_{n-1} + (1-\alpha) \cdot \bar{s} + \sqrt{(1-\alpha^2)} \cdot s_{x_{n-1}} \\ d_n &= \alpha \cdot d_{n-1} + (1-\alpha) \cdot \bar{d} + \sqrt{(1-\alpha^2)} \cdot d_{x_{n-1}} \end{aligned} \tag{21}$$

where s_n and d_n are the new speed and direction of the MN at time interval n; α is the tuning parameter used to vary the randomness; s and d are constants representing the mean value of speed and direction as n; and s_{xn-1} and d_{xn-1} are random variables from a Gaussian distribution. Totally random values are obtained by setting $\alpha = 0$ and linear motion is obtained by setting $\alpha = 1$. Intermediate levels of randomness are obtained by varying the value of α between 0 and 1.

Two parameters – alpha and the mean speed – were used to change user movements. The model's parameters were the following:

- $s_{x_{n-1}}$: Gaussian random variable (mean = 0, variance = 10).
- $d_{x_{n-1}}$: Gaussian random variable (mean = 0, variance = 1.2 rad).
- α: variable, or constant 0.75.
- $\bar{s}$: mean speed, constant 50, or variable.
- $\bar{d}$: the main direction $\pi/2$ rad.

The main speed was constantly 50, while α was altered between 0.4 and 0.9. As the value of α rises, the user's movement becomes less randomly, and more linearly. The one and two ring based predictions are far less accurate than the other two models (see *Fig. 10*). The difference is more remarkable than it was in the first simulation, because the user's movement is more realistic, which cannot be handled efficiently by the symmetrical simple models. By increasing alpha – as the movement becomes more deterministic – the error rate of all predictions decreases. The differences between Markov and handover vector random walk models cannot be seen in *Fig. 10*, the two models are depicted separately in *Fig. 11*.

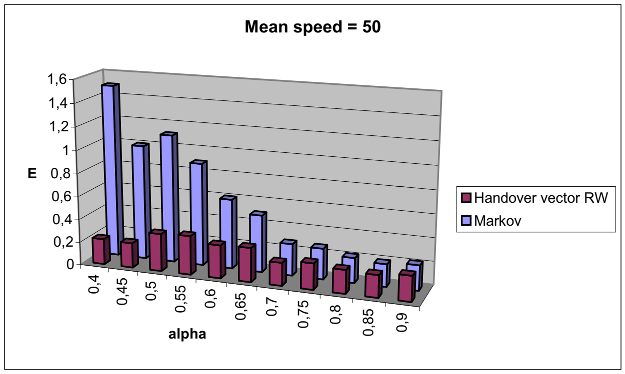

Fig. 10. Prediction error of the models in function of alpha

For small alpha values, Markovian model based prediction performs less accurately than the handover vector method. The reason of the performance deterioration is that the handover vector is able to distinguish six directions, while the Markovian model can take into consideration only the main directions.

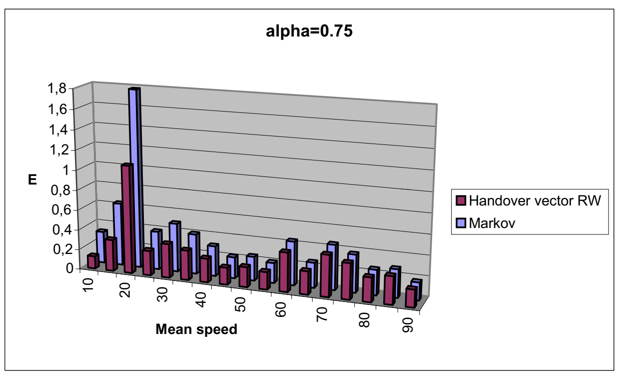

Fig. 11. Prediction error of the Markovian and the random walk model in function of alpha

The results of our next simulation, where $\alpha = 0.75$, and main stream varied between 10 and 90, can be seen in *Fig. 12*. The main speed parameter influences user mobility, the relationship is nearly linear. Like in the former case, symmetric models performed badly, only the Markovian and the handover vector random walk were depicted. According to the results in *Fig. 12*, both models perform well, although the handover random walk has a slight advantage.

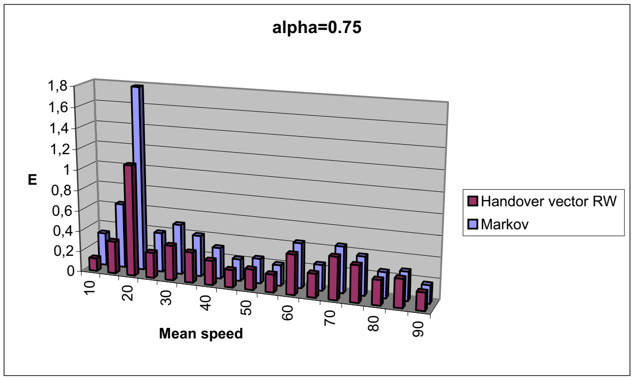

Fig. 12. Prediction error of the Markovian and the random walk model in function of the mean speed

The accuracy of the prediction of both one and two rings symmetric random walk models is significantly less than that of the other two models. The difference is higher than in the first simulation. The reason for this is that the users movement is more realistic than in the first simulation, which the simple models cannot cope with.

6. Conclusions

In this paper we have introduced a new Markovian mobility model, and calculated the most probable future number of pedestrian users for the radio cells based on this model and the ring concept. We compared the accuracy of the model to the random walk model by simulation. The obtained results and equations can be utilised in resource-reservation-based CAC algorithms, paging algorithms, etc.

The parameter (q) of the random walk model is easy to determine based on measuring the actual number of handovers in the network. The parameters of the Markov model can also be calculated based on handover measurement, while the directions of the handover events, and the time interval between them are needed.

Prediction based on our extended Markov model proves to be as precise as the handover vector random walk method, meanwhile the respective calculations and equations are much simpler.

The results show that the accuracy of the prediction depends on the range of the forecast. The two-ring concept takes into consideration the users moving at higher speed, therefore it provides more accurate information for the CAC algorithm than the one-ring-based forecast. We are working on the determination of the optional forecast distance in function of the mobile terminals speed in the network. There is also a trade-off among model complexity (e.g. the number of states in the Markov model) and accuracy. Although we have investigated our extended Markov model with three states, it is interesting how the complexity and the accuracy of a two dimensional Markov model reduce, when the number of states (initially six for each adjacent cell) is reduced. Based on the characteristics of a given radio cell, the minimal appropriate number of Markov model states can be calculated (e.g. in a radio cell covering a segment of a highway there are two probable directions, so a Markov model with two states is adequate) for each radio cell in the system, so the resultant equations will be less complex.

We also plan to investigate the precision of other models, which are appropriate for modelling vehicle traffic, such as the Gaussian model and the fluid flow mobility model.

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