A New Threshold-Based Predictive Reservation Scheme for 2D Wireless Environments

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Abstract—**Recently there has been a lot of research and development in wireless networking and mobility management, with the main purpose of connection handling between mobile hosts and base stations or access points. QoS guarantee is a very important issue in wireless communications, when mobile nodes move among different coverage areas. This paper presents a general prediction technique based both on the analysis of Cell Stay Time and on the direction probabilities of hand-in and hand-out events of mobile nodes from wireless cells. User mobility has been analyzed, in order to reduce passive resource reservations, with a high gain in system utilization. In particular, a threshold-based algorithm is presented, trying to take into account the mobility behavior of mobile users, through the analysis of a directional probabilities matrix. The performances of the 2D wireless system have been evaluated in terms of prediction error and system utilization; in addition, some comparisons with older prediction schemes have been made.**

***Index Terms*—QoS, WLAN, MIP, Smooth Random Mobility Model, Predictive Reservation, Threshold-based**

I. Introduction

The satisfaction of QoS guarantees in wireless environments is a key issue in the networking scenario, especially when dealing with handover events, when service continuity has to be maintained and quality degradations must be avoided.

One of the mechanisms that guarantees a good connection level is the passive reservation policy [1,5,8] based on the in-advance (or passive) reservations concept. In mobile systems this policy can be applied with certain protocols only if some information about user mobility behaviour is known [2,3,8].

The choice of a mobility model has great impact on the obtained results and they can be unrealistic if the model is not appropriate. We employed the Smooth Random Mobility Model (SRMM) [4] for a two-dimensional set of cell clusters because it makes user movements smoother and more realistic than previous random models, relating speed and direction changes. In addition, it leads to a general set of analytical expressions, which can be used for different wireless environments (urban, rural, etc.).

The new proposed idea does not depend on the specific mobility model, because it is only based on the knowledge of two important statistics: the Cell Stay Time (CST) distribution and the Hand-off Directions Probabilities values (HDP) that can be always obtained; HDP values are necessary in order to consider future positions of mobile hosts. So, combining CST and HDP information, a prediction technique is introduced: a threshold-based algorithm, which uses CST and HDP values to dynamically select the number of cells in which the bandwidth is to be reserved in advance, is proposed. It is shown that the obtained results are better than those of the previously proposed reservation schemes, based on a static reservation policy such as presented in [13]. The threshold-based algorithm performs better, because it is able to better adapt itself to dynamic mobile host movements.

This paper is organized as follows: section II gives a brief overview of the SRMM, used as reference for host movements; the threshold-based algorithm is presented in section III; simulation results and conclusions for a 802.11 scenario are respectively summarized in sections IV and V.

II. Smooth Random Mobility Model

Choosing an appropriate mobility model plays an important role in bandwidth assignments and network dimensioning; many works in the literature face this problem, but most of them are based on some simplifications about user behavior and do not lead to any analytical expression. The obtained results can be unrealistic if the model is not appropriate. This work employs the Smooth Random Mobility Model (SRMM) proposed in [4] for a two-dimensional set of cell clusters. It relates speed and direction changes and it leads to a general set of analytical expressions, which can be used for different wireless scenarios. The main concepts of the SRMM are two stochastic processes for direction φ and speed v: their values are correlated to the previous ones, in order to avoid unrealistic patterns and speed/direction changes; e.g. if a user is moving fast, a direction change cannot have high φ variations. Speed and direction changes follow two Poisson processes and different typical patterns or environments can be modeled by setting some parameters, like the set of preferred speeds. This model is also based on a set of preferred speeds in the range [v_{min} , v_{max}] and a mobile host moves with constant speed until a new target speed v^* is chosen by the stochastic process, so it accelerates/decelerates in order to reach v^*. The set of preferred speeds $\{v_{pref0}, v_{pref1}, \ldots, v_{prefn}\}$ is also defined in order to obtain a non-uniform speed distribution like the one depicted in figure 1, with $p(v_{pref}) = p(v_{pref0}) + p(v_{pref1}) + \ldots + p(v_{prefn}) < 1$, $v_{pref0} < v_{pref1} < \ldots < v_{prefn}$ and v_{max} is a fixed threshold.

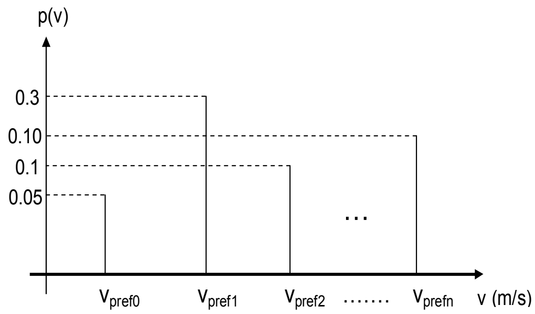

Figure 1. Example of probability distribution for *n* preferred speeds.

Let t^* denote the time at which a speed change event occurs and a new target speed $v^*=v^*(t^*)$ is chosen. Now, an acceleration $a(t^*) \neq 0$ must be set. It is taken from:

$$p(a) = \begin{cases} \dfrac{1}{a_{\max}} & \text{for } 0 < a \le a_{\max} \\ 0 & \text{else} \end{cases} \qquad (1)$$

if $v^*(t^*) > v(t^*)$, or from

$$p(a) = \begin{cases} \dfrac{1}{a_{\max}} & \text{for } a_{\min} \le a < 0 \\ 0 & \text{else} \end{cases} \qquad (2)$$

if $v^*(t^*) < v(t^*)$. Acceleration a is set to 0 if $v^*(t^*)=v(t^*)$. Then, two other variables are used: a_{max} and a_{min}. The first one represents the maximum possible acceleration and the second one the maximum possible deceleration. In discrete instant times of Δt duration, the new speed $v(t)$ is changed according to the uniformly accelerated motion as follows:

$$v(t) = v(t-\Delta t)+a(t)\cdot \Delta t \qquad (3)$$

until $v(t)$ achieves $v^*(t)$. a_{max} and a_{min} values are fixed to the values specified in table I in the section III. More details on SRMM model can be found in [4].

III. CST Analysis and Threshold-based Prediction Algorithm

A. Passive reservation problem

As discussed earlier, the guarantee of a certain level of QoS in a wireless scenario (the 802.11 in this work) is a key issue in the world of networking. The Mobile ReSerVation Protocol (MRSVP) [1] is able to make active and passive reservations [12] in order to pre-reserve a certain amount of bandwidth. In our work we have considered Mobility Dependent and Independent Predictive services (MDP and MIP respectively) [7]. In particular MIP users require the absence of service degradations during hand-off events. The proposed idea is now illustrated. First of all, many simulations have to be carried out in order to obtain some information about user behavior. Under a chosen mobility model (the SRMM in our case) and a certain cell coverage topology, the average Cell Stay Time (CST) can be observed, as in previous works [12], under the hypothesis of an exponentially distributed Call Holding Time (CHT). It can be seen that the CST distribution can be well approached by a Gaussian distribution, with different means and standard deviations depending on some fixed mobility parameters. The Kolmogorov-Smirnov (KS) normality test [9] was carried out to evaluate the correctness of a Gaussian approximation of CST distributions under the SRMM. Different *p-values* [9] were obtained, showing that there is a negligible error if a Gaussian approximation is employed for the CST distribution.

As mentioned above, we used the SRMM and mobile hosts follow the stop-turn-and-go behavior with toroidal topology as in [4], with two preferred speeds v_{pref0}=0 Km/h, $v_{pref1}=v_{max}$ Km/h. A Poisson call arrival time distribution was considered. With the knowledge of the CHT and CST distributions, the number of visited cells (including the active one) C_e can be evaluated. Unfortunately, without directional information about user mobility patterns, the predicted value of C_e may be only used to make passive reservations in a circular way, on a cluster with a radius of C_e cells, centered in the cell where the call has been admitted (the active cell); so, following the same approach as [12], only the value of C_e can be obtained a-priori with a negligible amount of error and the number of required passive reservations C_r for MIP services in a two-dimensional environment with hexagonal coverage areas increases with a polynomial trend, such as follows:

$$C_r=3\cdot C_e\cdot(C_e-1) \qquad (4)$$

This work introduces a novel algorithm, based on some additional information about user directional behavior, so the above problem can be avoided and the value of C_r can be decreased, making it nearer to C_e, depending on the adopted reservation threshold. Figure 2 depicts the difference between a circular reservation policy and a directional one, with an appreciable gain in terms of the number of cells affected by passive reservations.

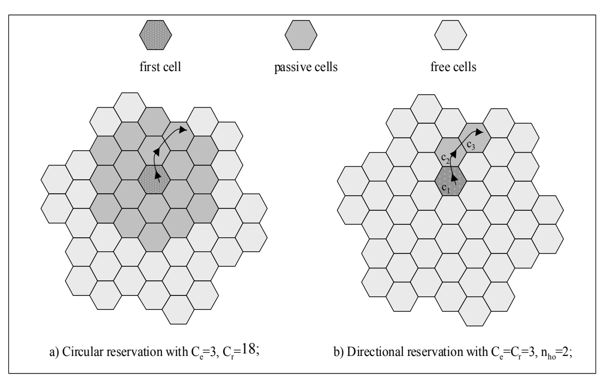

Figure 2. Examples of circular reservation (a) and directional reservation (b) with hexagonal approximation.

B. Threshold based approach

A generic coverage area, generally with a circular shape, can be approximated with an n-edge regular polygon as depicted in figure 3 (n can be considered as an input control parameter):

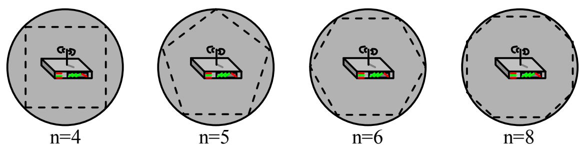

Figure 3. Possible Access Point (AP) coverage area approximations with regular polygons.

As can be seen from figure 3, for higher values of n better approximations can be reached. At this point, a set S_{ho} of n possible movement directions can be obtained: let us indicate them with $d_1 ... d_n$, where:

$d_j = \theta \cdot (2 \cdot j-1)/2$ *rad.*, $\theta = 2\pi/n$ *rad.* and $j=1..n$,

so $S_{ho}=\{d_1, .., d_n\}$ and $|S_{ho}|=n$.

Once n has been chosen, a square nxn mobility probabilities matrix M can be defined with the following elements: $M(x,y)= p_{x,y}=p_{CMIP}(x,y)=p(y \in S_{ho}/x \in S_{ho})$, that is to say $M(x,y)$ indicates the probability of generic user $\boldsymbol{i}$, for a fixed mobility model, of handing-in a wireless cell from direction $x \in S_{ho}$ and handing it out to direction $y \in S_{ho}$ after μ_{CST} amount of time. Note that matrix M depends only on the adopted mobility model and network cells subdivision and it is the same for all users in the system. Matrix M has the hand-in directions on the rows and the hand-out ones on the columns. It can be filled out through a first campaign of simulations. Generally the $M(x,y)$ elements are statistically distributed and not symmetric, so they have to be represented in the right way as explained later. If λ indicates the mean of CHT of MIP users, the predicted number of hand-off events for user $\boldsymbol{i}$ $h_i = C_{ei}-1$ can be obtained such as shown in [12]. Let vh_i be an information support-array, where $vh_i[k]$ with $k=1..h_i$ indicates the information about k-th future hand-off of user i; i.e. each entry in the array vh_i, $vh_i[k]$, can be a pointer to a list of tuples $\{cell\_id, from, to, p_{cell\_id}\}$ for k-th hand-off event. *cell_id* is a cell identifier and $from \in S_{ho}$, $to \in S_{ho}$ are respectively the hand-in and hand-out directions for the *cell_id* cell. p_{cell_id} is the probability that the user will be under the coverage of the *cell_id* cell after the k-th hand-off; the algorithm predicts *to* directions, given *cell_ids*, *from* directions and p_{cell_id} values. Let δ be an input threshold for the cell estimation phase (as for n, δ is an input control parameter that affects system performances, as illustrated in section IV). As we will see later, if knowledge of the first hand-off cell is used for example, with one of the policies proposed in [10,11], then the following threshold-based predictor algorithm can be performed in order to obtain the complete set of predicted cells that MIP user $\boldsymbol{i}$ will probably visit, starting from the *2-nd* hand-off event and going on until the h_i-th one:

THRESHOLD-BASED PREDICTOR

```
//for every predicted hand-off event of user i
for (int k=2; k ≤ h_i; k++) {
  //index on the cells of the k-th hand-off event
  int l=1;
  //for each cell of the current k-th hand-off event
  while (l ≤ vh_i[k].size()) {
    //let us analyze the current l-th tuple in the k-th element
    current_tuple= vh_i[k].elementAt[l];
    //the hand-in direction is known
    curr_hand_in_dir= From(current_tuple.to);
    //probability of user i of being in current cell after the
    //(k-1)-th hand-off
    p_curr=current_tuple.p_cell_id;
    //find the "more suitable" hand-out candidate cells over
    //the possible n hand-out directions
    for (int p=1; p ≤ n; p++) {
     //the probability of hand-out on direction p after having
     //handed in on direction curr_hand_in_dir is evaluated
     curr_prob=M(curr_hand_in_dir, p)*p_curr;
     //threshold based comparison
     if (curr_prob ≥ δ^f(k)){
       //the current cell can be considered a valid candidate
       id=Cell_id( current_tuple.cell_id, p);
       //the v_hi vector must be updated
       create_a_tuple{curr_hand_in_dir, p, id, curr_prob};
       append the tuple in vh_i[k+1];
     }
    }//for p
    l++;
  }//while l
  clean vh_i[k+1] from duplicates;
}//for k
create an empty cell identifiers list p_cells;
//extract cell ids from tuples and append them to p_cells
for (int k=1; k<=t_i; k++) {
  for (int l=0; l<vh_i[k].size(); l++) {
    current_tuple=vh_i[k].elementAt(l);
    append current_tuple.cell_id to p_cells;
  }
}
return p_cells. //returns the identifiers of predicted cells
```

C. System parameters

As discussed earlier, the candidate cell for the first hand-off must be discovered, because no hand-in direction is available when a flow is admitted in a cell. With one of the approaches of [10,11] the current mobility direction $\boldsymbol{d_j} \in S_{ho}$ of user $\boldsymbol{i}$ is obtained and the term $first\_id= =first\_Cell\_id(current\_id,\ d_j)$ can be obtained, by an appropriate function *first_Cell_id()* that evaluates the identifier of the cell that user $\boldsymbol{i}$ will visit (*current_id* is the identifier of the current cell). As shown in previous works [13], this approach leads to a negligible amount of error for the first prediction (around 3%-4%). At this point, a tuple *{first_id,_ , d_j, 1}* can be created and appended in *$vh_i[1]$*; the *from* direction cannot be discovered because user ***i*** has started his flow in the current *first_id* cell, without handing it in from any direction while p_{first_id}=1 because the probability of hand-out from *first_id* cell during the first hand-off is 1. Let's suppose that the elements of *M* are constant values, so the main aim now is prediction making for all the cells contained in the list of *$vh_i[k]$*, with *$k=2..h_i$*. Each tuple in *$vh_i[k]$* contains the hand-in direction, the cell identifier and the probability of user ***i*** of being in the cell after the *(k-1)-th* hand-off. Through a threshold-based comparison the algorithm must decide what are the cells that user *i* will visit with higher probability when handing-out the cell of the *l-th* tuple of *vh_i [k]*, *$l=1...vh_i[k]$.size()* with a well-known hand-in direction; the hand-in direction *curr_hand_in_dir* belongs to S_{ho} and it specifies a unique row of *M*. The algorithm calculates the probability of hand-out from the current cell on direction *p* after having handed-in from direction *curr_hand_in_dir* when the probability of being in the previous cell before the current hand-off is p_{curr}: if the obtained value is higher than $\delta^{f(k)}$, then the cell that is adjacent to the current one on direction *p* must be considered as a possible future cell and a tuple {*from*, *p*, *adjacent_p_cell, curr_prob*} is appended in *vh_i [k+1]*. The exponent *f(k)* is a function of *k*. In this work it is assumed that *f(k)=k* but other kind of functions can be considered in the future; since $0<\delta<1$, the comparison threshold $\Delta=\delta^k$ goes decreasing for higher values of *k* and a higher number of cells can be selected. The function "***cell_id Cell_id(cell_id current_id, direction to)***" returns the identifier of the cell adjacent to ***current_id*** cell on ***to*** direction. The function "***direction From(direction to)***" translates the hand-out direction ***to*** of the previous cell in the hand-in direction of the next cell. A cleaning routine must be executed after finishing appending elements in *$vh_i[k]$* position, because of possible duplications of cell identifiers. A different approach has been followed in [13]: a static reservation policy has been adopted and the HDP matrix has been applied through the selection of a prefixed number of columns without considering the gap in direction probabilities. For details to see [13].

TABLE I
SIMULATION PARAMETERS OF THE SRMM.

Number of preferred speeds	n_{pref} = 2
Preferred speeds (m/s)	v_{pref0} = 0; v_{pref1} = 13.9
Maximum acceleration (m/s^2)	a_{max} = +2.5
Minimum acceleration (m/s^2)	A_{min} = -4
Preferred speed probability p_v	p_{v0}=0.1; p_{v1}=0.8
Direction change prob. p_φ	p_f=0.1

The hypothesis of *M* composed of constant values is not suitable: after many simulations and tests (following the approaches of [9]), we can conclude that the elements *M(x,y)* can be well approached with a Gaussian approximation, so *M(x,y)* is a couple of values, the mean and the standard deviation of the obtained distribution, as depicted in figure 4. So in the proposed pseudo-code $M(x,y)=N(\mu_{x,y},\sigma_{x,y})$.

IV. PERFORMANCES EVALUATION

Our network consists of 7 clusters of cells, like the ones depicted in figure 2; users moves toroidally, according to the SRMM, with the same mobility parameters of table I. An exponentially distributed CHT with mean λ=180s was considered. Simulation results are compared with those of the static-scheme of [13] and some enhancements are shown.

0.0137, 0.0061	0.0244, 0.0128	0.2779 ,0.0429	0.3663, 0.0497	0.3034, 0.0476	0.0256, 0.0132
0.0325, 0.0166	0.0132, 0.0044	0.0399 ,0.0198	0.3700, 0.0525	0.5056, 0.0554	0.0549, 0.0251
0.3708, 0.0545	0.0430, 0.0203	0.0125 ,0.0030	0.0316, 0.0174	0.0521, 0.0227	0.5054, 0.0552
0.3692, 0.0462	0.2798, 0.0464	0.0249 ,0.0133	0.0129, 0.0060	0.0248, 0.0138	0.2994, 0.0461
0.3743, 0.0554	0.5094, 0.0581	0.0440 ,0.0210	0.0328, 0.0173	0.0127, 0.0031	0.0437, 0.0213
0.0318, 0.0170	0.0426, 0.0223	0.5094 ,0.0579	0.3769, 0.0556	0.0427, 0.0212	0.0145, 0.0071

Figure 4. Directional probabilities matrix M in terms of μ,σ for the mobility parameters of table I, with n=6.

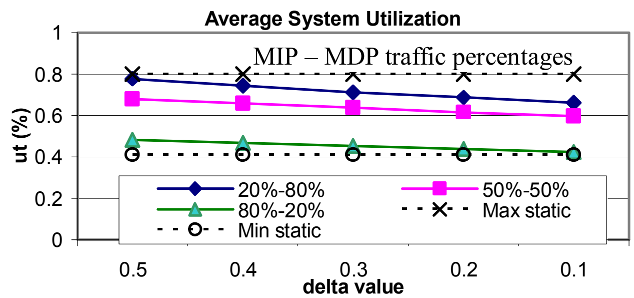

Figure 5. Average system utilization for different δ values.

Figure 5 shows the course of the average system utilization versus δ values. Dashed lines represent the maximum and the minimum obtained values for the static policy of [13]. System utilization decreases for lower δ values: a higher number of predicted cells is foreseen, so a higher amount of passive reserved bandwidth is necessary. Utilization also decreases for higher percentage of MIP traffic, because of the higher number of passive reservations and less MDP traffic. As discussed above, higher values of predicted cells lead to a negligible prediction error, but the system utilization noticeably decreases. The maximum value of the static case is obtained with the prediction sequence 1-1-1 (i-j-k are the number of desired predicted cells for first, second and third hand-off respectively) and 20%-80% traffic percentages for MIP and MDP users, while the minimum with 3-2-1 and 80%-20%. As shown in the figure, the performances in terms of system utilization are comparable for static and dynamic cases, but the second one performs better for higher percentages of MIP flows.

In figure 6 another comparison between the static scheme of [13] and the threshold-based one is made, in terms of the average number of predicted cells for different hand-off events. Dashed lines refer to the static scheme for different i-j-k values as in [13], while continuous ones refer to the threshold-based scheme for different δ values. The arrow indicates decreasing values of δ. The average number of per-flow predicted cells does not depend on the erlang (requests/s) value and the different continuous curves refer to δ=0.60 δ=0.20 and δ=0.05. For the static scheme the curves for 1-1-1, 1-2-3 and 3-3-3 sequences are illustrated. It is shown that introducing the threshold, a gain in terms of predicted cells is obtained, with some improvements in system utilization, as described earlier: the difference between the two policies is more evident for lower δ values and higher hand-off number.

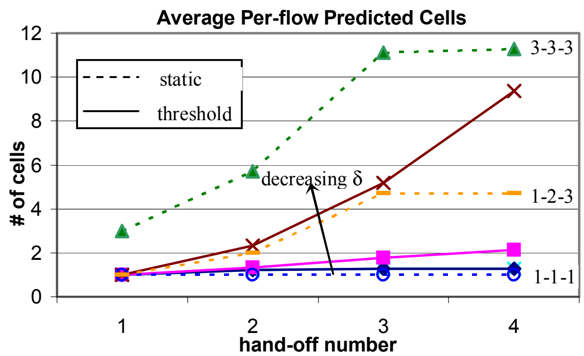

Figure 6. Average number of predicted cells per-flow for different i-j-k and δ values.

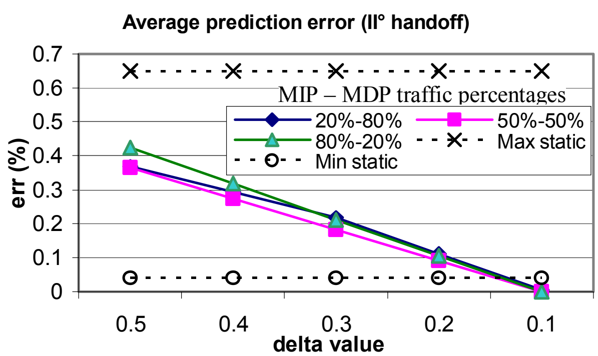

Figure 7. Average prediction error for second hand-off events with static and threshold-based schemes.

Figure 7 shows the committed error on predicting future cells for the 2nd hand-off event using dynamic policies (for the static case, only the maximum and minimum obtained values are shown): the error has a decreasing course because, as earlier discussed in section III, decreasing δ values lead to a higher number of predicted cells; that is to say an MIP user has a lower probability of suffering a reservation outage after a hand-off event. Both curves start with high error values (near to 64% and 42%) that drastically reduce (until 5% and 0). In the dynamic case, for δ=0.1, the number of predicted cells is always near to 6, so there are no errors in choosing the right hand-out direction (circular reservation). Setting δ to lower values can make the error negligible but MIP system utilization cannot be acceptable if compared to the MDP one. Among the simulated input prediction sequences, the *ijk=123* sequence offers a good trade-off between error (under 10%) and utilization, as well as the value of δ=0.2. This suggests that the choice of low δ values (like 0.2 or 0.3) offers a good trade-off between error and system utilization.

V. CONCLUSIONS

A novel threshold-based prediction algorithm has been proposed, in order to manage the QoS in a 2D wireless environment. It faces the problem of pre-reserving passive bandwidth for MIP flows over the cells that compose the system, trying to reduce the wastage of passive resources. It is based on the knowledge of the average CST and some information about user mobility behavior. The proposed scheme implements a dynamic matrix analysis through an input threshold value, solving the problem of previous static schemes that have to specify the number of cells on which passive reservations must be made for different consecutive hand-off events. Many simulations have been carried out in order to make a comparison with previous schemes. Simulations results have revealed that the threshold-based scheme performs better than the previous ones, because it reduces the average number of predicted cells,with a slight decrease in errors. In addition, it dynamically decides how many cells must be involved in the pre-reservation phase.

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