A new 2D Direction-Based Predictive Reservation Scheme for WLAN Environments with Passive Advanced Reservations

Floriano De Rango, Peppino Fazio, Salvatore Marano
D.E.I.S. Department, University of Calabria, Italy, 87036
e-mail: {derango, pfazio, marano}@deis.unical.it

Abstract—**In last years there has been a lot of research and development in wireless communications and mobility management, with the main purpose of connections handling between mobile hosts and base stations or access points, when different coverage areas are visited. This paper presents a novel 2D reservation scheme for WLANs; a general prediction technique based both on the analysis of Cell Stay Time (CST) and on the direction probabilities of hand-in and hand-out events of mobile nodes from wireless cells is outlined. In particular, a threshold-based algorithm is presented, trying to take into account the mobility behavior of mobile users, through the analysis of a Hand-off Directional Probabilities (HDP) matrix. Users' mobility has been analyzed, in order to reduce passive resource reservations, with a high gain in system utilization. In particular, an integrated architecture able to make active and passive reservations has been employed as a possible application of the proposed approach. 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—**MRSVP, WLAN, MIP, Smooth Random Mobility Model, Predictive Reservation**

I. Introduction

This work is based on a wirelessLAN 802.11 scenario, where MIP users [1,5,8] make service requests to the access points, requiring some QoS guarantees, like low delay-jitter or low call dropping probability during hand-off events; the only way for avoiding service degradations or disruptions during a mobile session is to make in-advance reservations (i.e. passive reservations) [1,5], having some informations about users' mobility behaviour [2,3,8].

The choice of an appropriate mobility model plays an important role in bandwidth assignments; many works in literature face this problem, but most of them are based on some simplifications about users' behaviour and do not lead to any analytical expression. The mobility model has a heavy impact on the obtained results and they can be unrealistic if the model is not appropriate. We employed the Smooth Random Mobility Model (SRMM) proposed in [4] for a two-dimensional set of cell clusters; this model makes users' movements smoother and more realistic than previous random models, because it relates speed and direction changes; in addition it leads to a general set of analytical expressions, that can be used for different wireless environments (urban, rural, etc.).

In [12] a prediction technique based on cell stay time (CST) evaluation of a mobile user under a Random Way Point mobility model is proposed. In this work a formula that bind speed, cell radius and variation around the average speed is calculated. However no more realistic two dimensional (2D) mobility model has been considered and just the CST has been evaluated. This approach is not suitable for a 2D WLAN environment. On the basis of the previous work weakness, a novel technique of general application has been proposed and and it does not depend on the specific mobility model; it is based on the knowledge of two important statistics: the CST distribution and the Hand-off Directions Probabilities values (HDP); in [8] it is shown that the CST random variable, under the SRMM, follows a Gaussian trend, with a mean and a variance that depend on the input mobility parameters, strictly related to users' behaviour. In addition to the CST statistic, HDP values are necessary in order to consider future positions of mobile hosts. Until now, in the literature [2,3,11], no heavy contribution is given to the multi-step mobility prediction in wireless cellular environments. In this paper, combining CST and HDP informations, a multi-step and threshold-based prediction algorithm is proposed for a two-dimensional environment: it uses CST and HDP values to dynamically select the future cells where to reserve passive bandwidth; 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 is more performing because it is able to better adapt itself to dynamic mobile hosts' movements.

This paper is organized as follows: section II gives a brief overview of the Mobile RSVP protocol (applied in our work to make passive reservations) and the SRMM, used as a reference for hosts' movements; the threshold-based algorithm is presented in section III; simulation results and conclusions are respectively summarized in sections IV and V.

II. MRSVP and SRMM

In order to handle users' mobility and to offer guaranteed services (independent from mobility) the ReSerVation Protocol has been extended with the MRSVP [1]; in this way, hand-off events can be managed in an adequate manner and mobile users can make reservation requests over more than one cell, by their proxy agents: there are local proxy agents (for active reservations handling) and remote proxy agents (which deal with passive reservations). An active reservation is made by a user only on the current access point (for *Mobility Dependent Predictive* class, as we see later), while passive reservations are made only on the remote cells that the user will visit during its connection (only users belonging to *Mobility Independent Predictive* class requests passive reservations). A MRSVP connection starts with a proxy-discovery protocol phase, with which the user can become aware of the addresses of its remote agents; then a resource request can be made, which will reach the net sender, in order to begin data-packets transmission. After the proxy addresses are discovered, users send active_RESV messages to their local access points and passive_RESV messages to their remote access points, so the system must effect an admission control, in order to accept or refuse users' requests. When a user moves from a coverage area to another one, the hand-off event is managed by making a new request (MDP class) or by a reservation switch (MIP class): the reserved resources in the old access point are released in both cases and, if the user belongs to MIP class, the passive resources can be assigned by switching to an active reservation. For more details about MRSVP to see [1].

A. MIP and MDP Classes

Internet best-effort service does not offer any guarantee about available bandwidth, network propagation delays, jitter and packet delivery. As consequence, there have been different research groups that tried to define some service models, in order to deal with applications variety in packet networks. Integrated Services (IS) networks are the results of such kind of works, as described in [1,8]. In a real network, resources reservations can be made by protocols, in order to satisfy QoS requirements, accounting the inherent time varying environmental conditions, more marked in radio communications (e.g. fading). In IS networks, each flow can receive different QoS, which must be negotiated at the beginning of sessions, between flows and network, by the RSVP or the MRSVP in mobile scenarios [1]. There are three provided service classes [5,8]: Mobility Independent Guaranteed (MIG, for hard and intolerant applications, that need absolute guarantees on packet delays), Mobility Independent Predictive (MIP, for tolerant real-time applications, that can suffer limited bounds on packet delays) and Mobility Dependent Predictive (MDP, for applications that can suffer continuous QoS degradations or connection droppings). In this paper, only MDP and MIP classes have been considered. As earlier discussed, the MRSVP is used for exchanging state information of wireless networks and it can offer soft QoS (adaptive QoS) for MIP and MDP services; so they have two different management in terms of admission control and bandwidth assignments. MIP services use a pre-reservation phase to reserve bandwidth for mobile host in the current cell and in the cells that the mobile host will probably visit (passive and active reservations) [7].

B. Smooth Random Mobility Model

The choice of an appropriate mobility model plays an important role in bandwidth assignments and networks dimensioning; many works in literature face this problem, but most of them are based on some simplifications about users' behavior and do not lead to any analytical expression. So, the choice of the mobility model has a heavy impact on the obtained results, that 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 clusters; this model makes users' movements smoother and more realistic than previous random models, because it relates speed and direction changes; in addition it leads to a general set of analytical expressions, that 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 with high speed, 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, such as:

$$p(v_{pref})=p(v_{pref0})+p(v_{pref1})+\ldots+p(v_{prefn})<1, \qquad (1)$$

with $v_{pref0}<v_{pref1}<\ldots<v_{prefn}$ and v_{max} is a fixed threshold.

Let t^* denote the time at which a speed change event occurs and a new target speed $v^*=v^*(t^*)$ is chosen. More details on SRMM model can be found in [4].

III. Cell Stay Time and Direction Aware Threshold-Based Algorithm

First of all, many simulations have to be carried out in order to obtain some information about users' 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 a Call Holding Time (CHT) exponentially distributed. 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] has been led out to evaluate the correctness of a Gaussian approximation of CST distributions under the SRMM; different *p-values* have been obtained [9], showing that there is a negligible error if a Gaussian approximation is employed for the CST distribution.

As mentioned above, we used the SRMM with stop-turn-and-go behavior for mobile hosts, with toroidal topology as in [4] and two preferred speeds $v_{pref0}=0$ Km/h, $v_{pref1}=v_{max}$ Km/h; a Poisson call arrival time distribution has been considered. With the knowledge of the CHT and CST distributions, the number of "future visited" cells (including the active one) C_e can be evaluated as follows. It is possible to express the p.d.f. of CST in the following way:

$$f(x_{CST}) = \frac{1}{\sqrt{2\pi}\sigma_{CST}} e^{-\frac{1}{2}\left(\frac{x-\mu_{CST}}{\sigma^2_{CST}}\right)} \quad (2)$$

where μ and σ are the obtained values of mean and standard deviation respectively; so $X_{CST} \sim N(\mu_{CST}, \sigma^2_{CST})$.

So it is possible to evaluate the error of considered CST and to make a prediction based on confidence intervals and confidence levels, considering the worst case *cell outage probability* (COP). It is possible to select a cell stay time T_{cst} for a mobile host so that $Prob(X< T_{cst}) <1\text{-}COP$, where X is normally distributed. T_{cst} is called a (1-COP)*100% upper confidence bound for X. If the average call holding time T_{cht} is known, it is possible to consider the term C_e as:

$$C_e = \left\lceil \frac{T_{cht}}{T_{cst}} \right\rceil . \quad (3)$$

Unfortunately, without directional information about users' 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), under the worst case hypothesis of mobile hosts moving straight-forward; so, following the same approach of [12], from eq.3 only the value of C_e can be a-priori obtained 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 polynomial trend:

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

Without the analysis of the possible directional movements of the generic mobile host there will be a lot of resources wastage, due to the enormous amount of passive pre-reserved bandwidth over C_r cells, which increases for longer calls or for higher values of v_{max}.

This work introduces a novel algorithm, based on some additional informations about users' directional behavior and the above problem can be avoided with a lower value of C_r, making it nearer to C_e, depending on the adopted reservation threshold (as it will be shown). Figure 1 depicts the difference between a circular reservation policy and a directional one.

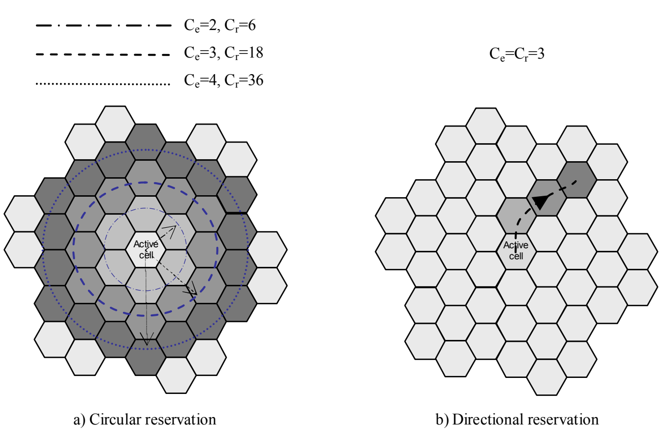

Figure 1. Examples of circular reservation (a) and directional reservation (b) with hexagonal (n=6) approximation.

The proposed idea is now illustrated. A generic coverage area, generally with a circular shape, can be approximated with a *n*-edge regular polygon as depicted in figure 2 (*n* is considered as an input control parameter); for higher values of *n* better approximations can be reached. A set S_{ho} of *n* possible movement directions can be then obtained.

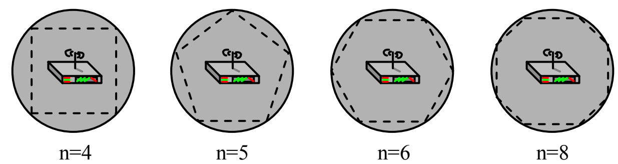

Figure 2. Possible Access Point (AP) coverage area approximations with regular polygons.

Let indicate them with $d_1 \dots d_n$, where:

$$d_j=\underline{\theta}\cdot(2\cdot j\text{-}1)/2 \ rad., \ \underline{\theta}=2\pi/n \ rad. \text{ and } j=1..n, \quad (5)$$

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

Once *n* has been chosen, a square *nxn* hand-off directional probabilities (*HDP*) matrix *M* can be defined as follows:

$$M(x,y)=p(y\in S_{ho} \ / \ x\in S_{ho}) \quad (6)$$

that is to say $M(x,y)$ indicates the probability of a generic user *i*, for a fixed mobility model, of handing-in a wireless cell from direction $x\in S_{ho}$ at time $t=t_0$ and handing it out to direction $y\in S_{ho}$ after $N(\mu_{CST}, \sigma_{CST})$ 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. The 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 addicted 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. If λ indicates the mean of CHT of MIP users, the predicted number of hand-off events for user *i* $h_i = C_{ei}\text{-}1$ can be obtained as in from eq.3.

Let vh_i be an information-support array, where $vh_i[k]$ with $k=1..h_i$ indicates the informations about the *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 the *k-th* hand-off event, where:

- *cell_id* is a cell identifier;
- $from \in S_{ho}$, $to \in S_{ho}$ are respectively the hand-in and hand-out directions for the *cell_id* cell;
- p_{cell_id} is the probability that user will be under the coverage of the *cell_id* cell after the *k-th* hand-off.

The algorithm predicts *to* directions for each tuple, starting from *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 will be illustrated in section IV). If the knowledge of the first hand-off cell is approached, 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 ***i*** will probably visit, starting from the *2-nd* hand-off event and going on until the h_i*-th* one ($h_i \geq 2$):

DIRECTION AWARE 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 of vh_i
    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 n possible 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{id, curr_hand_in_dir, p, 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.
```

As earlier discussed, 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 ***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 ***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 its flow in the current *first_id* cell, without handin-in it 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 us hypotize that the elements of M are constant values, so the main aim is now the 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 {*adjacent_p_cell, from*, p, *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; the power operation is necessary in order to take into account the increase of prediction error for higher values of k: 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. The static scheme does not account for M structure and a prediction sequence *i-j-k* for the first three hand-off events must be specified as an input parameter, specifying the prediction of i cells for the first hand-off, j and k for the second and third ones. For details to see [13]. When repeating all the steps h_i*-1* times, a cleaning routine must be executed after finishing appending elements in $vh_i[k]$ position, because of possible duplications of cell identifiers; the same results can be obtained if the append function avoids duplicates. The prediction result is the set of cell identifiers of the tuples for each vh_i list.

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 hypotesis of *M* composed by 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 5. So in the proposed pseudo-code $M(x,y)=N(\mu_{x,y},\sigma_{x,y})$. From these values of directional distributions, it can be seen that the average number of next predicted cells decreases for higher δ as illustrated in table II.

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

TABLE II
AVERAGE NUMBER OF PREDICTED CELLS FOR DIFFERENT THRESHOLD VALUES

δ values	0.6	0.5	0.2	0.1	0.05
pred. cells	1	1.76	1.76	5.18	5.18

IV. PERFORMANCES EVALUATION

Our network consists of 7 clusters of cells, like the ones depicted in figure 1; users moves toroidally, according to the SRMM, with the same mobility parameters of table I. An exponentially distributed CHT with mean λ=180s has been considered. Simulation results are compared with those of the static-scheme of [13] and some enhancements are shown.

Figure 6 illustrates the average system utilization if MIP and MDP flows can be admitted; the threshold δ is fixed to 0.01: if only MDP traffic is allowed (so MIP-MDP percentages are set to 0 and 100 respectively) there is an increasing trend for higher erlang (requests/s) values from 75.6% to 95.4%, because of the higher active assigned bandwidth; the utilization goes diminishing for increasing percentages of MIP flows, because of the higher presence of passive and unused bandwidth but the trend is always increasing for the same previous reason; perhaps, as it can be seen, if only MIP traffic is admitted into the system, the utilization drastically goes down and it is slightly decreasing for higher erlang values, because of the higher presence of unused passive bandwidth (from a minimum level of 10.34% of 25 erlang to a maximum level of 13.11% of 5 erlang). For the other values of δ (we simulated from 0.01 to 0.6) the "only-MDP" scenario is not affected, because there are no passive reservations to do, while for intermediate percentages (040-060 and 060-040) the utilization does not decrease in a sensible way; if "only-MIP" traffic is allowed in the system, the utilization falls down to 5-6% for δ=0.6. An increase of the threshold value means, as we see later, a higher value of predicted cells, so a higher presence of passive pre-reservations, if "only-MIP" traffic is allowed. The comparison with the static policy of [13] with "only-MIP" traffic is also shown; dashed lines represent the maximum and minimum values under the static policy, obtained for 25 erlang and *i*=1 or *i*=3 respectively: the static policy performs better in terms of utilization for *i*=1, but this value is not proposeable because, as shown in figure 7, it leads to a heavy amount of prediction error (over 50%) beginning from the second hand-off. For other *i* values (e.g. *i*=3) the utilization falls down, under the minimum obtained with the proposed scheme.

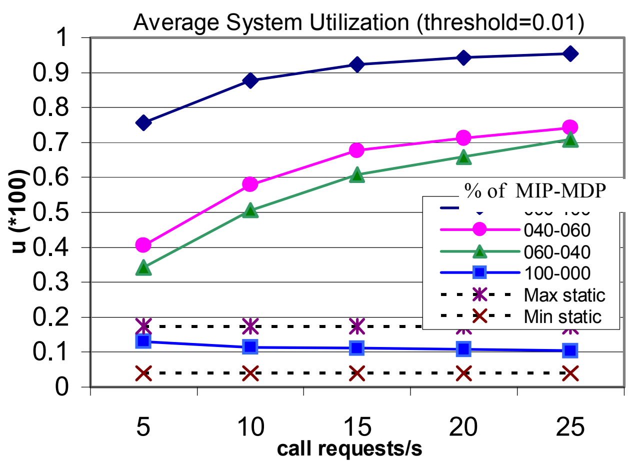

Figure 6. Average system utilization for different erlang values.

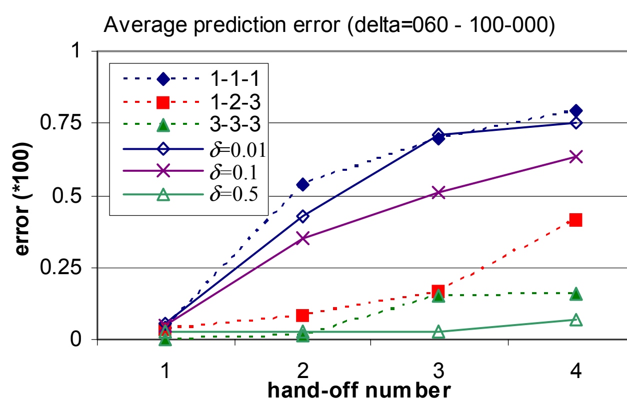

Figure 7. Average prediction error for different hand-off events with static and threshold-based schemes.

Figure 7 depicts the committed error on predicting future cells only for MIP users: for the *n*-th hand-off event, it is calculated as the ratio between the number of MIP users that handed-in a cell during the *n*-th hand-off event without finding an available bandwidth pre-reservation and the number of total

MIP users that made the *n*-th hand-off. The best results are evident for δ=0.01, because the error is maintained below 8% for all hand-off events. For other combinations of *i-j-k* values there is always a δ value that offers better performances. This suggests that the choice of low δ values (like 0.01 or 0.05) offers a good trade-off between error and system utilization.

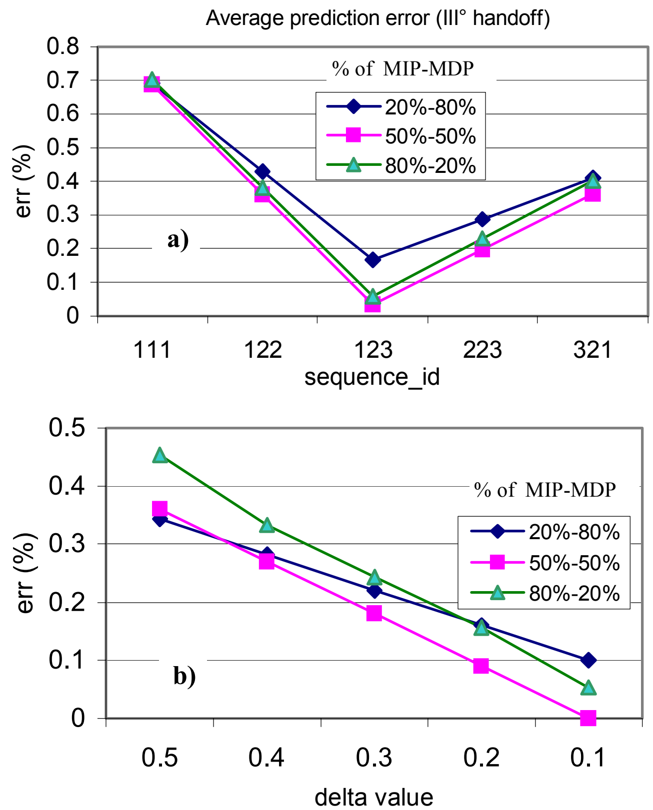

Figure 8. Average prediction error for third hand-off with (a) static reservation, (b) dynamic reservation.

Figures 8a and 8b depict the average error for the 3rd hand-off event: the same trend of the previous curves (2nd hand-off event) is not obtained for the static case. Further for decreasing values of δ the number of predicted cells for the 3rd hand-off also increases, this is not verified for the static case, because the considered sequences, after the *ijk=123* one, assume a lower number of predicted cells for the 3rd hand-off than the *ijk=123* sequence. For this reason the same trend of the 2nd hand-off case is not obtained and the error goes increase for the sequences *ijk=223* and *ijk=321*. Also in this case, more suitable results are obtained for *ijk=123* and δ=0.1 or δ=0.05, because the error is lower than 10% for these input values.

The error on the first hand-off prediction is not referred here because it is not based on the proposed techniques; the first hand-in direction can be predicted as [10,11]. An increasing number of predicted cells for the static case is compatible with the problem of the increasing prediction error for consecutive hand-off events: the error committed in the prediction of the *i-th* hand-out direction propagates itself while predicting the *(i+1)-th* one; if an increasing number of predicted cells is assumed, then the error decreases.

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 minimize the wastage of passive resources. It is based on the knowledge of the average CST and some informations about users' 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, while leading the error to slightly lower levels; in addition it dynamically decides how many cells must be involved in the pre-reservation phase.

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