A 2D Cell Stay Time and Movement Direction-Based Reservation Scheme for WLAN Clusters with Active and Passive Advanced Reservations

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

ABSTRACT

QoS guarantee is a very important issue in wireless communications, when mobile nodes move among different coverage areas. This paper presents a novel 2D reservation scheme for WLAN environments. 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 directional probabilities matrix. An integrated architecture able to make active and passive reservations has been employed as a possible application of the proposed approach. Many simulations have been carried out and a performance analysis has been performed, finding a good trade-off between bandwidth utilization and prediction error.

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 to avoid service degradations or disruptions during a mobile session is to make in-advance reservations (i.e. passive reservations) [1,5], accounting for users mobility behavior [2,3,8]. We employed the Smooth Random Mobility Model (SRMM) proposed in [4] for a two-dimensional set of cell clusters. The proposed technique is of general application and does not depend on the specific mobility model; it is based on the knowledge of two important statistics: the Cell Stay Time (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, depending on the preferred speeds of users, strictly related to their behavior; in addition to the CST statistic, HDP values are necessary in order to consider future positions of mobile hosts; so, combining CST and HDP informations, a prediction technique is proposed for a two-dimensional environment. A threshold-based algorithm, that uses CST and HDP values to dynamically select the cells, where to in advance reserve the bandwidth, is proposed.

This paper is organized as follows: section II gives a brief overview of the Mobile RSVP protocol (applied in our work in order to make passive reservations) and the SRMM; the 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 (RSVP) has been extended with the MRSVP [1]; hand-off events can be managed in an adequate manner and mobile users can make reservation requests over more than one cell, by their local and remote proxy agents; an active reservation is made by a user only on the current access point, while passive reservations are made only on the remote cells that the user will visit during its connection. A MRSVP connection starts with a proxy-discovery phase, with which the user can be acquainted with 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 can be managed by making a new request or by a reservation switch: the reserved resources in the old access point are released in both cases and, in the latter case, passive resources can be assigned by switching to an active reservation. For more details about MRSVP 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 and to offer to mobile hosts a service "better than best-effort". 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 protocol or the MRSVP protocol 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, subject to certain 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. MRSVP protocol is used for exchanging state information of wireless networks and it can offer soft QoS (adaptive QoS) for MIP and MDP services; 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 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. The main concepts of the SRMM are two stochastic processes for direction φ and speed v: their values are related 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^*. 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 informations 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 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 has been 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 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); so, following the same approach of [12], only the value of C_e can be a-priori obtained with a negligible amount of error. The number of required passive reservations C_r for MIP services in a two-dimensional environment with hexagonal coverage areas increases with polynomial trend, such as follows:

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

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, 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 1 depicts the difference between a circular reservation policy and a directional one.

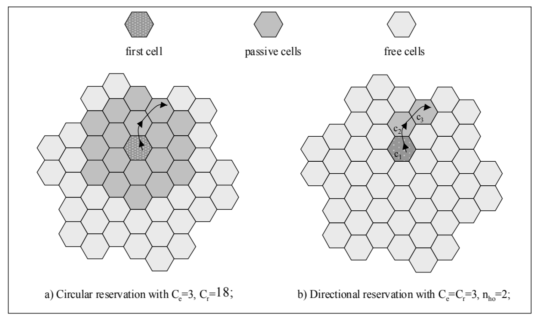

Figure 1. Examples of circular reservation (a) and directional reservation (b) with hexagonal cell approximation.

A coverage area, generally with a circular shape, can be approximated with a n-edge regular polygon as depicted in figure 2 (n can be considered as an input control parameter):

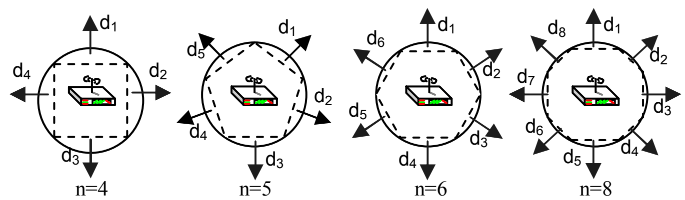

Figure 2. Possible Access Point (AP) coverage area approximations.

As it can be seen from figure 2, for higher values of n better approximations can be reached. A set S_{ho} of n possible movement directions can be then obtained: let us indicate them with $d_1 ... d_n$, where $d_j=\underline{\theta}\cdot(2\cdot j-1)/2$ *rad.*, $\underline{\theta}=2\pi/n$ *rad.* and $j=1..n$, so $S_{ho}=\{d_1, .., d_n\}$ and $|S_{ho}|=n$. After n has been chosen, a square nxn mobility probabilities matrix M can be defined as:

$$M(x,y) = p(out\ to\ y \in S_{ho}\ t=t_0+CST\ /\ in\ from\ x \in S_{ho}\ t=t_0).$$

That is to say $M(x,y)$ indicates, for a fixed mobility model, the probability that a generic user i will be handed-out to direction $y \in S_{ho}$ after CST (a normally distributed value) amount of time, if it was handed into current wireless cell from direction $x \in S_{ho}$. 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 $h_i = C_{ei}-1$ can be obtained such as shown in [12], as the ratio between λ and CST (normally distributed). Let vh_i be an information support-array, where $vh_i[k]$ with $k=1..h_i$ indicates the informations 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 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); the following steps are performed in order to obtain the complete set of predicted cells that MIP user $\boldsymbol{i}$ will probably visit during an active connection:

A. Evaluation of first hand-off possible direction and cell identifier

After the initialisation of vh_i with h_i "*to-null*" pointers, the algorithm must start with predicting cells for the first hand-off. Since no hand-in direction is available when a flow is admitted in a cell, matrix M cannot be used for a prediction on the first hand-off, so the algorithm evaluates the current mobility direction $\boldsymbol{d_j} \in S_{ho}$ of user $\boldsymbol{i}$ in the *current_id* cell with one of the approaches of [10, 11] and, assuming that user i will probably follow direction d_j until the first hand-out event, 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 following direction $\boldsymbol{d_j}$ from the current position; in the simulation tool, the implementation of the above function depends on the data structures used for representing the network topology, while in a real network it can be obtained through an appropriate signalling protocol. 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 $\boldsymbol{i}$ has started his 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.

B. Evaluation of possible directions and cells identifiers from 2-nd to hi-th hand-off events

Let us assume for now that the elements of M are constant values; the main aim is now the prediction making for all the cells contained in the list of $vh_i[k]$, with $k=1..h_i-1$; the pseudo-code below resumes the adopted policy when predicting cells for user $\boldsymbol{i}$ and it is fully described in the following:

THRESHOLD-BASED ALGORITHM

```
//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 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.
```

The whole procedure must be repeated h_i-*1* times (k goes from 2 to h_i because for the first hand-off event the prediction has already been made); so the k index scans vh_i until the h_i-*th* position (C_{ei}-*1* times); a prediction must be made for each cell of the $vh_i[k]$ list ($|v_{hi}[k]|$ is n in the worst case); each tuple in $vh_i[k]$ contains the hand-in direction, the cell identifier and the probability of user $\boldsymbol{i}$ 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* (obtained by a *From()* function that translates hand-out directions into hand-in ones) belongs to S_{ho}, so 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 $\Delta=\delta^{f(k)}$, 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 $[k+1]$ ($p=1..n$, so the probability evaluation is made n times, as the number of elements on a row of M). The exponent $f(k)$ is a function of k (let see next section, where different functions are considered); the power operation is necessary in order to take into account the increasing of prediction error for higher values of k. After the considerations above we can conclude that the computational complexity of the proposed scheme, in the worst case, is polynomial: $O(C_e \cdot n^2)$.

In the pseudo-code above some functions are introduced: let "***cell_id Cell_id(cell_id current_id, direction to)***" be a function that, given a cell identifier ***current_id*** and a hand-out direction ***to***, returns the identifier of the cell adjacent to ***current_id*** cell on ***to*** direction; let "***direction From(direction to)***" be a function that translates the hand-out direction ***to*** of the previous cell in the hand-in direction of the next cell. 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. It must be outlined that the prediction scheme is totally independent from the chosen mobility model (the SRMM in our case) and only M gives to it the right knowledge about users' mobility behavior. M can be derived for the desired mobility model.

The hypotesis of M composed by constant values is not suitable: after many simulations and tests (following the approaches of [9]), it can be concluded that the elements $M(x,y)$ can be well approached with a Gaussian distribution, so $M(x,y)$ is a couple of values, the mean and the standard deviation of the obtained distribution, as depicted in figure 3. So in the proposed pseudo-code $M(x,y)=N(\mu_{x,y}, \sigma_{x,y})$.

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 3. Directional probabilities matrix M in terms of μ,σ for the mobility parameters of [4], with n=6.

IV. PERFORMANCES EVALUATION

Our network consists of 7 clusters of wireless cells (figure 1); users move toroidally (only MIP users are considered), according to the SRMM, with the same mobility parameters of [4]. 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.

First of all, some considerations about the input parameters of the proposed algorithm are needed; in our simulations we considered 4 different expressions for the exponent function $f(k)$: a) $f(k)=1$; b) $f(k)=\alpha k$; c) $f(k)=\alpha/k$ and d) $f(k)=(\alpha k)^{-1}$, with α>0, in order to appreciate the different behaviors of the algorithm by varying Δ structure and how δ is weighted for consecutive values of k (i.e. consecutive hand-offs). Since δ is an input parameter, a preliminary analysis must be made in order to determine its admissible values (in terms of upper and lower bounds), in function of k and α.

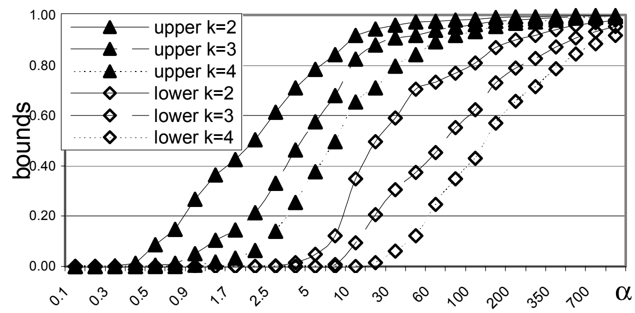

Figure 4. Upper and lower bounds of δ for $f(k)=\alpha/k$.

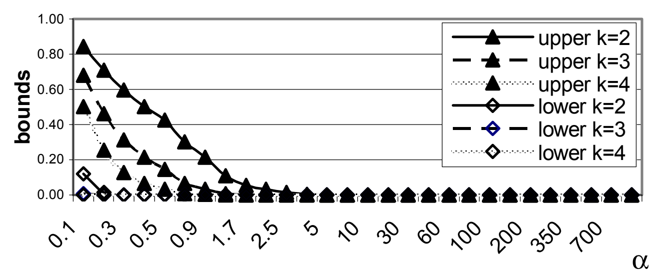

Figure 5. Upper and lower bounds of δ for $f(k)=(\alpha k)^{-1}$.

Figure 4 shows the obtained thresholds for $f(k)=\alpha/k$ and it can be seen that for higher values of k, the admissible region "shifts to the right", becoming less sensible to lower values of α. This kind of analysis is necessary for simulation results, because it gives an idea of the admissible values of δ that can be given as input parameter values for the performances evaluation. Figure 5 gives the same overview for $f(k)=(\alpha k)^{-1}$ and it can be seen how the admissible region goes decreasing its area for higher values of k. For space limitation reasons the admissible regions of the other kinds of exponent (cases a and b) are not shown here, but it must be outlined that for $f(k)=1$ there is, obviously, no dependence on α and for $f(k)=\alpha k$, there is no dependence on k. The upper and the lower bounds are evaluated for the different kinds of functions considering that the algorithm always chooses the maximum or the minimum value of M. Once the admissible values of δ are evaluated, different campaigns of simulations have been carried out, in order to appreciate the correctness of the proposed algorithm in terms of prediction error and system utilization. The committed prediction error for the first hand-off is not presented here because, as explained in section III, the algorithm starts its prediction from the second hand-off and the error for the first step is well negligible (about 2%-3%).

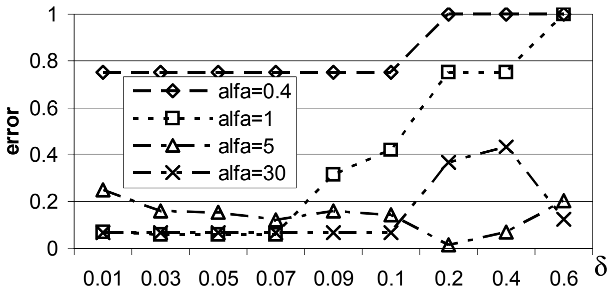

Figure 6. Prediction error for 2nd hand-off (k=2) and $f(k)=\alpha/k$.

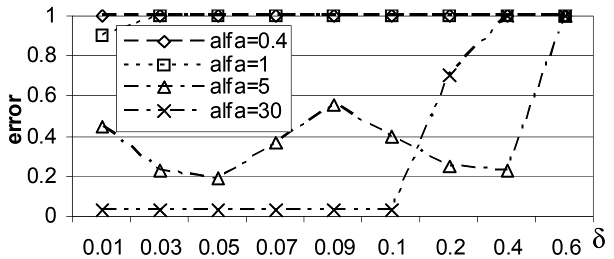

Figure 7. Prediction error for 3rd hand-off (k=3) and $f(k)=\alpha/k$.

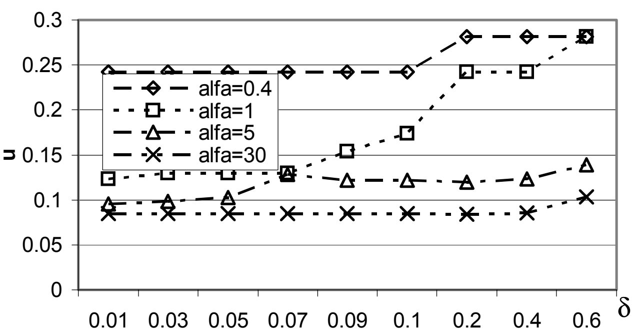

Figure 8. Average system utilization for $f(k)=\alpha/k$.

Figure 6 and 7 show the average error on predicting future cells for second and third hand-off (k=2 and k=3 respectively) with $f(k)=\alpha/k$. As it can be seen, when α is fixed and δ is outside the admissible region no changes occur on the obtained values (e.g. α=0.4 and δ=0.01÷0.1), as demonstrated in figure 4. The two figures show that better results can be obtained with α=30 and low values of δ, in spite of average system utilization, that falls below 10%, as depicted in figure 8 (where AP average utilization $\underline{u}$ is defined as the ratio between the average active bandwidth $\underline{B}$ and the AP capacity C, $\underline{u}=\underline{B}/C$). This is due to the fact that for higher alfa values, a higher number of cells is predicted, so the error decreases, but the amount of passive reserved bandwidth becomes not negligible. In order to increase system utilization, MDP additional traffic must be admitted into the system [12] and some kind of passive bandwidth multiplexing policies might be considered. The function $f(k)=\alpha/k$ performs better than the other ones in terms of prediction 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 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, in this way it dynamically decides how many cells must be involved in the pre-reservation phase. Many simulations have been carried out in order to observe the obtained performances. Simulations results have revealed that the threshold-based scheme performs better if a dynamic exponent function is considered and the obtained prediction error is negligible for second and third hand-off (less than 8%).

REFERENCES

[1] A.K.Talukdar, B.R.Badrinath, A.Acharya, "MRSVP: A Resource Reservation Protocol for an Integrated Services Network with Mobile Hosts," *Wireless Networks Kluwer Journal*, pp.5-19, 2001.

[2] M.M.Zoonozi, P.Dassanayake, "User Mobility Modelling and Characterization of Mobility Patterns," *IEEE Journal on Select.Area on Comm.*, vol.15, no.7, 1997.

[3] T.liu, P.Bahl, I.Chlamtac, "Mobility Modelling, Location Tracking,and Trajectoty Prediction in Wireless ATM Networks", *Journal on Select.Area on Comm.*, vol.16, no.6, Aug.1998.

[4] C.Betstetter, "Mobility Modeling in Wireless Networks: Categorization, Smooth Movement, and Border Effects," *ACM SIGMOBILE Mobile Computing and Communications Review*, Vol. 5, Issue 3, pp. 55–66, July 2001

[5] V.Bharghavan, K-W.Lee, S.Lu, S.Ha, J-R.Li, D.Dwyer, "The TIMELY Adaptive Resource Management Architecture," *IEEE Personal Communications Mag.*, pp.20-31, Aug.1998.

[6] A.Alwan, R.Bagrodia, N.Bambos, M.Gerla, L.Kleinrock, J.Short, and J.Villasenor, "Adaptive Mobile Multimedia Networks", *IEEE Personal Comm. Magazine*, Apr.1996, pp.34-51.

[7] Talukdar A. K., Badrinath B.R. and Acharya A., "On Accomodating Mobile Hosts in an Integrated Services Packet Network", *In the Proceedings of the IEEE INFOCOM '97*, April.

[8] F. De Rango, P.Fazio, S.Marano, "Cell Stay Time Prediction for Mobility Independent Predictive Services in Wireless Networks," IEEE Wireless Communications and Networking Conference (WCNC2005), New Orleans, Los Angeles, USA, 13-17 March 2005.

[9] M.A. Stevens, R.B. D'Agostino, "Goodness of Fit Techniques", Marcel Dekker, New York 1986.

[10] C.F. Lin, A.G. Ulsoy, "Vehicle Dynamics and External Disturbance Estimation for Future Vehicle Path Prediction", Proceedings of the American Control Conference, Seattle Washington 1995.

[11] Achir, M.; Ghamri-Doudane, M.; Pujolle, G, "Predictive resource allocation in cellular networks using Kalman filters" on *IEEE International Conference Communications (ICC '03)*, Vol.2, 11-15 May 2003, pp.974 – 981.

[12] F. De Rango, P.Fazio, S.Marano, "Mobility Independent and Dependent Predictive Services Management in Wireless/Mobile Multimedia Network," *IEEE Vehicular Technology Conference 2004 Fall (VTC Fall 2004)*, Los Angeles, CA, USA, Sept.2004.

[13] F. De Rango, P.Fazio, S.Marano, "Mobility Independent Predictive Services in WLAN Networks with Predictive Reservation Policy under a 2D Mobility Model," to appear on *Wireless Telecommunication Symposium (WTS'06)*, 27-29 Apr., Pomona, California, USA, 2007.