A New Markov-Based Mobility Prediction Scheme for Wireless Networks with Mobile Hosts

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

Abstract— **Recently, mobile communications need to benefit a good level of Quality of Service (QoS), since communications guarantees are mandatory during active flows. Passive resources are used to ensure service continuity when mobile hosts are moving among different coverage cells. In this work the attention is focused on wireless services in cellular networks, where the hand-over effects need to be mitigated, through an appropriate reservation policy. The whole considered system is modeled through a distributed set of Hidden Markov Chains (HMC) and the related theory is used to design a mobility predictor, as the main component of the proposed idea, which does not depend on the considered transmission technology (GSM, UMTS, WLAN, etc.), mobility model or vehicular scenario (urban, suburban, etc.). MRSVP has been used in order to realize the active/passive bandwidth reservation in the considered network topology and many simulation campaigns have been carried out in order to estimate the correctness of the proposed algorithm, also in terms of CDP and CBP.**

Keywords- MRSVP, MIP, Mobility Prediction, Citymob, Hidden Markov Model, Distributed Prediction, .

I. INTRODUCTION

Quality of Service (QoS) constraints have to be respected in wireless communications and the hand-over issues are relevant when hosts change coverage areas during their active sessions. Since mobile computing is becoming popular in last years due to the advantages of wireless communications (in terms of comfort and reliability), the effects of mobility have to be reduced and in this work we consider Mobility Independent Predictive (MIP) users [1], which request reliable connections to the networks with a guaranteed service continuity after hand-over events: low call-dropping probability and low delay-jitter must be ensured. The only way to avoid service degradations during hand-over events is represented by passive-reservations making [1], [2], [3]: that is to say, when a mobile user makes a service request on the current coverage cell, the admission control and rate adaptation [4] should ensure fairness and bandwidth availability on all the cells that the mobile hosts will probably visit during its session. So, a prediction scheme is mandatory, in order to know which cells a user will visit during its Call Holding Time (CHT). The Mobile ReSerVation Protocol (MRSVP) is able to guarantee the right communication among the interested coverage cells, while the predictor gives the possibility to know which are the cells where the mobile host will hand-in. The mobility model has a heavy impact on the obtained results: in this paper we employed the Citymob for Roadmaps (C4R) mobility generator in order to appreciate prediction performance when mobility traces are extracted from real roadmaps. The proposed technique is completely general and does not depend on the specific coverage technology: we do not care if mobile hosts are using UMTS or WLAN, for example, for their connections. In this work, the integration between a reservation protocol, like MRSVP, and Markov processes leads to a new distributed prediction scheme, which has been tested through some deep campaigns of simulations. The paper is organized as follows: section II gives a deep overview of the existing related work, section III proposes the new prediction scheme and gives a description of the MRSVP and the basics of Hidden Markov Chains theory, section IV shows simulations results, then section V concludes the paper.

II. STATE OF THE ART

In Integrated Services (IS) networks, each flow can receive different QoS, which must be negotiated at the beginning of sessions, between flows and net, by the ReSerVation Protocol or the MRSVP or DRSVP protocol in mobile scenarios [7,9,10]. In the wired network environment, several techniques have been proposed in academia and industrial community in order to provide QoS to applications. Since mobility and resource management are critical to supporting mobility and providing QoS in wireless networks, it is very important to accurately describe movement patterns of mobile users in wireless cells. Two prediction-based resource reservation techniques are proposed in [11]. These techniques consider the Wiener prediction theory and the time series analysis in order to make a predictive resource reservation under non-Poisson and/or non stationary arrival processes, arbitrary distributed call and channel holding time and arbitrary per-call resource demands. In [12], a hierarchical user mobility model based on an appropriate pattern matching and Kalman filtering is presented. This approach permits to get the necessary information for advance resource reservation and optimal route establishment in wireless ATM networks. In this work a two-level user mobility model is used to represent the movement behavior at global and local levels. In [14] a framework to estimate service patterns and to track the mobile users is proposed. This work is based on historical records and predictive patterns of mobile users that permit to estimate the next cells into which a mobile user will possibly move. The same authors proposed a new location management scheme for the mobile terminals (MTs) roaming across multi-tier PCS systems with different technologies or protocols [15]. A scheme for resource reservation and call admission control algorithm have been proposed in [16]. In this work the authors make use of hand-off prediction to deploy bandwidth resources to the mobile users among the visited cells. The proposed reservation scheme is based on the location estimation of the mobile user, on the instantaneous variation of the speed and the direction of mobile stations. In [18] a prediction technique based on the cell stay time (CST) evaluation of a mobile user under a Random Way Point mobility model is proposed. A formula that binds speed, cell radius and variation around the average speed is calculated and resource reservation techniques have been proposed. In [19] the authors propose a prediction-based location management scheme for locating a MH, which depends on its history of movement pattern. A Multilayer Neural Network (MNN) model for mobile movement prediction is designed to predict the future movement of a MH. The performance of the method has been verified for prediction accuracy by considering different movement patterns of a MH and learning accuracy. In this work, instead, a distributed prediction algorithm is proposed; in particular, the main efforts are: a) each coverage cell uses a particular Markov chain (with a limited number of states) in order to describe and predict local user movements; b) MRSVP has been integrated with Markov chains in order to realize a complete prediction scheme; c) training of Markov chains is made by taking into account local trajectories and each predictor is specialized for the specific mobile environment.

III. THE NEW PREDICTION SCHEME

As known from [1], MRSVP gives the possibility to manage hand-off events in an adequate manner and mobile users can make reservation requests over more than one cell, by their proxy agents: an active reservation is made by a user only on the current coverage cell, while passive reservations are made on the remote cells that the user will visit during its connection (users belonging to Mobility Independent Predictive class, MIP, request passive reservations). When a user moves from a coverage area to another one, the hand-off event is managed by a reservation switch: the reserved resources in the old access point are released and the passive resources can be assigned by switching to an active reservation.

A. MRSVP protocol and wireless system modeling

Let C be the set of coverage cells of the considered wireless network, $C=\{c_1,c_2,\ldots,c_c\}$ with $||C||=c$, then for each cell $c_i \in C$, with a coverage radius cr_i, a set of neighboring cells $Adj(c_i)$ can be defined, on the basis of network topology and cell adjacencies. A generic coverage cell, generally with a circular shape, can be approximated with a n-edge regular polygon and n can be considered as an input control parameter. A set S_{ho} of n possible movement directions can be then obtained: let us indicate them with $d_1 \ldots d_n$, where $d_j=\underline{\theta}\cdot(2\cdot j-1)/2$ *rad.*, $\underline{\theta}=2\pi/n$ *rad.* and $j=1..n$, so $S_{ho}=\{d_1, \ldots, d_n\}$ and $||S_{ho}||=n$. In the classical approaches on cellular networks [22], n is set to 6, so in this work $||Adj(c_i)||=||S_{ho}||=6$, $\forall\ c_i \in C$. Let us suppose that each cell $c_i \in C$ has the availability of L bandwidth channels and each user occupies one channel in the current c_i: that is to say that the maximum number of active users in a cell is L. Our attention is not focused neither on the Call Admission Control (CAC) nor on the Bandwidth Reallocation Scheme (BRS) of the system, but only on the prediction of next neighboring cells, through a HMC. So, we considered the simplest implementation, which provides that each mobile user will receive the same bandwidth level, related to the assigned channel on the cell, for the entire flow duration and a cell can accommodate an active/passive request only if $l_{ci}<L$, where l_{ci} is the number of currently occupied bandwidth channels on cell c_i. Users mobility has been considered through [17]. At this point, in the passive reservation message of MRSVP an additional field "*res_ho*", indicating the number of residual predicted hand-over events, can be added and the active cell (where the call has originated) can evaluate the number of predicted hand-over events n_{ho}, as in [5]. Then, if $n_{ho}\geq 2$ (at least 1 hand-over events have been predicted), the active cell prepares a passive reservation packet to be forwarded to the predicted neighbor by setting $res\_ho=n_{ho}-1$. As defined in [1], when a cell receives a resource request, it has to perform the CAC: in the considered case it only verifies if $l_{ci}<L$. If there are no available channels ($l_{ci}=L$), then the request cannot be accepted and a RESV_NACK message is sent toward mobile host. If a channel can be assigned and c_i is the last predicted cell (*res_ho*==0), it only has to send a positive RESV_CONF message toward mobile host. On the other hand, if more hand-over events have been predicted (*res_ho*≠0) for the considered mobile host, the cell uses a HMC predictor to know which is the neighboring cell to forward a passive reservation message to, after the *res_ho* value has been decreased by 1; at the same time, the cell sends a RESV_CONF toward the mobile host. At this point, the active cell knows the bandwidth availability on the predicted path for the mobile host, if no RESV_NACK messages have been received. We hypothesize that, in the considered wireless cellular system, mobility management is performed by coverage cells. Now the proposed local predictor is described. A dedicated HMC is considered for each cell, which does not have knowledge of the whole system, as illustrated in fig. 1. The HMC for a generic cell $c_i \in C$ has a number of states equal to $n=||S_{ho}||$, that is to say each state is associated to a possible hand-off direction. In this case, for example, a state transition from s_1 to s_5 occurs if a mobile host enters the cell from d_1 and hands-out to d_5.

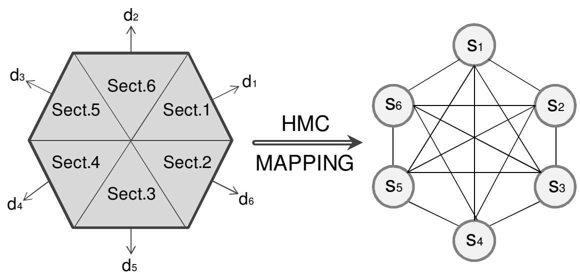

Fig. 1. An example of HMC structure for n=6.

A graph $G=<V,E>$ is associated to a local HMC, where V is the set of vertices and E is the set of edges. Each vertex $v_j \in V$ represents a hand-off direction $d_j \in S_{ho}$, then $||V||=||S_{ho}||=n$. The considered graph is complete (a mobile host may hand-out to any of the n available directions, independently from the hand-in direction), so:

$$E=\{(v_i,v_j)/\forall v_i,v_j \in V \;\; and \;\; v_i \neq v_j\}, \;\; \| E \| = \frac{\| V \| \cdot (\| V \| -1)}{2} \qquad (1)$$

At this point we considered the obtained graph as the state transition map of the HMC.

B. Hidden Markov chains background

As earlier described, in this work the MRSVP has been integrated with the Markov processes. In particular Hidden Markov Chains (HMCs) have been considered, because the passive reservation messages have to be sent only to the remote cells that a mobile host will probably visit: each intermediate coverage cell has to know which is the neighboring cell where the mobile host will hand-in. At this aim, each coverage cell has its own HMC predictor, which is used to predict future neighboring cells. The HMC is a statistical model used for describing generative sequences that can be characterized by an underlying process generating an observable sequence. Formally, a HMC can be described by a triplet λ as follows:

$$\lambda = (A, B, \pi) \; . \qquad (2)$$

Defining S as the set of possible states $S=\{s_1,s_2,\ldots,s_N\}$, with $||S||=N$ and V as the observations set $V=\{v_1,v_2,\ldots, v_M\}$ with $||V||=M$, then a finite state sequence $Q=q_1, q_2, \ldots, q_T$ and a corresponding observation sequence $O=o_1, o_2, \ldots, o_T$ can be defined, with $||Q||=||O||=T$. The first term in eq.2 is a transition array, which stores the probability of state j following state i, independent from time:

$$A=[a_{ij}], a_{ij}=P(q_t=s_j / q_{t-1}=s_i) \; . \qquad (3)$$

The second term is the observation array, storing the probability of observation k being produced from the state j, independent of t:

$$B=[b_i(k)], b_i(k)=P(x_t=v_k / q_t=s_i) \; , \qquad (4)$$

and π is the initial probability array:

$$\pi=[\pi_i], \pi_i=P(q_1=s_i). \qquad (5)$$

In addition to the Markov chain dependence property, for the HMC there is another assumption for the model, for which the output observation at time t is dependent only on the current state and it is independent of previous observations and states:

$$P(o_t / o_1^{t-1}, q_1^{t}) = P(o_t / q_t). \qquad (6)$$

In this paper, a HMC is used by each coverage cell to forward passive reservation messages to the predicted neighboring cell. Details about learning, evaluation and decoding can be found in [20], [21].

C. Learning, prediction and utilization

Based on classic theory on HMC and Baum-Welch algorithm [8], λ has to be determined, because it represents the triplet that defines the model for the proposed prediction scheme. Because observations of mobile hosts movements are possible (in our case by a system simulator), supervised training can be approached, because HMC inputs and desired outputs are known. Training observations consist in a set of hand-over direction sequences. Having a high number of training observations, the Maximum Likelihood Estimates (MLE) can be used for the evaluation of A, B and π as follows:

$$a_{ij}=P(s_i \mid s_j)=\frac{TR(s_i,s_j)}{TR(s_i)} \qquad (7)$$

$$b_i(k)=P(v_k \mid s_i)=\frac{OCC(v_k,s_i)}{TR(s_i)} \qquad (8)$$

$$\pi_i=P(q_1=s_i)=\frac{OCC(q_1=s_i)}{N(q_1)} \qquad (9)$$

where, $TR(s_i,s_j)$ is the number of observed transitions from state i to state j and $N(s_i)$ is the number of transitions from state s_i to any other state. A transition from s_i to s_j occurs when, in the training data, a mobile host hands-in a cell from direction d_i and hands-out to direction d_j. The term $OCC(v_k,s_i)$ in eq. 8 represents the number of occurrences of state s_i in the observations v_k. State s_i occurs in the observation v_k if direction d_i is contained in the *k-th* hand-over sequence of the training data. The term in eq. 9 represents the probability that state s_i (hand-over direction d_i) is the first observed state (q_1) in the training observations and it is evaluated as the ratio between the number of occurrences of s_i being the first observed state $OCC(q_1=s_i)$ and the number of total observations of first states $N(q_1)$. So, λ can be evaluated through a supervised training. At this point, given the HMC model expressed through the triplet λ, we need to evaluate $P(O|\lambda)$, that is to say the probability of the observation sequence O given the model λ. The probability of O for a specific state sequence Q can be expressed as:

$$P(O \mid Q,\lambda)=\prod_{t=1}^{T} P(o_t \mid q_t,\lambda)=b_{q_1}(o_1)\cdot b_{q_2}(o_2)\cdot \ldots \cdot b_{q_T}(o_T) \qquad (10)$$

and the probability of the state sequence is:

$$P(Q \mid \lambda)=\pi_{q_1} a_{q_1 q_2} a_{q_2 q_3} \ldots a_{q_{T-1} q_T} \qquad (11)$$

so:

$$P(O \mid \lambda)=\sum_{Q} P(O \mid Q,\lambda)\cdot P(Q \mid \lambda)=$$

$$=\sum_{q_1 \ldots q_T} \pi_{q_1} b_{q_1}(o_1)\cdot a_{q_1 q_2} b_{q_2}(o_2)\cdot \ldots \cdot a_{q_{T-1} q_T} b_{q_T}(o_T) \qquad (12)$$

If the forward-backward algorithm is introduced to evaluate the expression of eq.12, the complexity is reduced from $2TN^T$ to N^2T [8],[20]. The current state is represented by the hand-in direction d_i, and the HMC is consulted by its own coverage cell in order to know the predicted hand-out direction (for the first prediction the hand-in direction is substituted by mobile host born sector, where the call originated; sectors subdivision is illustrated in fig. 1).

IV. PERFORMANCE EVALUATION

Many simulations have been carried out in order to evaluate the performances of the proposed idea in terms of average prediction error, channel assignments, call dropping probability and call blocking probability. The considered scenario consists of a set of cell clusters, for a total of c=35 coverage cells, depicted in fig. 2 where, for example, real paths of Rome (centre Italy) have been considered through the C4R mobility simulator [17] with a 900x900 m^2 map. All the cells have the same coverage radius $cr_i=r,\ \forall\, i \in C$ and an exponentially distributed CHT with mean λ=180s has been considered. In the simulation scenario, each coverage cell offers L=20 channels and it is connected, by a switching subnet, to the net-sender. Border effects on mobility are neglected by ignoring mobile trajectories with paths outside the coverage set. Simulation time has been set to 3000s for each run.

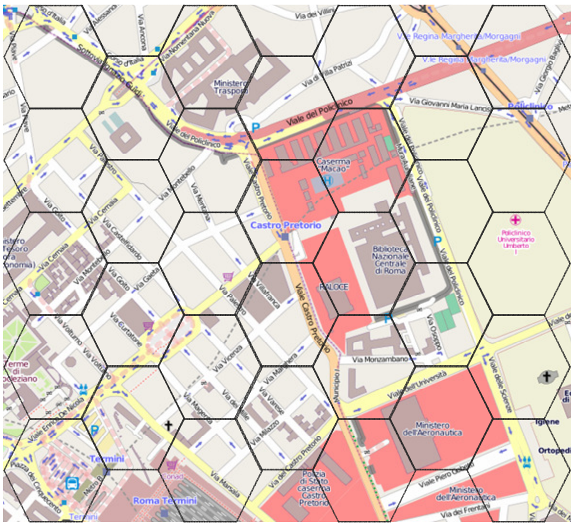

Fig. 2. Simulation map with c=35, cr_i=150m and L=20.

A first campaign of simulations has been carried out in order to obtain the appropriate training data. In particular, the proper size of the training set has been investigated and fig. 3 shows the trend of the prediction accuracy for different number of observations. Curves are shown for different values of training set dimension (from 50 to 300) and r has been set to 150m for space limitations.

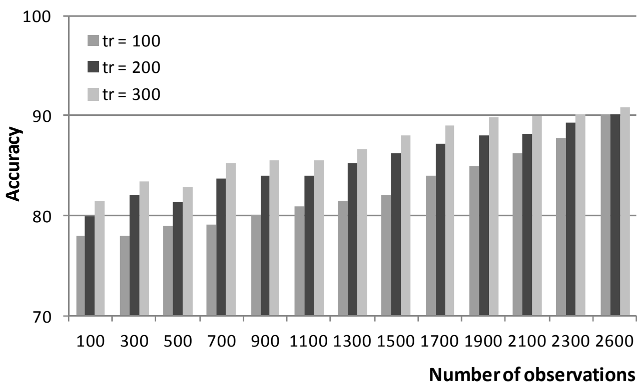

Fig. 3. Prediction accuracy or different training set dimensions (100, 200 and 300) and r=150m.

Prediction accuracy is evaluated as the ratio between the number of correctly predicted hand-overs observations and the number of total observations: the correctness of prediction is evaluated on all the observed hand-out directions. From fig. 3 it is evident how good results are reached, because each coverage cell has its own HMC and the training is made only on the possible hand-out directions that belong to the specific coverage. In addition, the dimension of the training data have to be carefully chosen, in order to avoid over-fitting phenomena [6],[13]. In our case, a training set of 200 items brings the predictor to acceptable performance in terms of prediction accuracy. Fig. 4 depicts the trend of the average channels utilization of the whole wireless system for different MIP traffic percentages: it represents the ratio between the number of channels assigned to MIP active calls and the total number of channels of the system (c*L=35*20=700). Different percentages of MIP traffic have been considered with different values of cell radius r, with a best-effort complementary traffic (no passive reservations are made for this kind of traffic). When MIP traffic increases, more passive reservations are made into the system, so a higher number of channels are, in-advance, reserved for the arriving mobile hosts. In this way a bandwidth wastage is introduced and channels utilization falls below 70%. No big differences are evident among the proposed schemes (the maximum gap is around 5%). For larger radio coverage, channels utilization decreases due to higher quantity of mobile hosts which have to be served, with a consequent increasing of passive reservations.

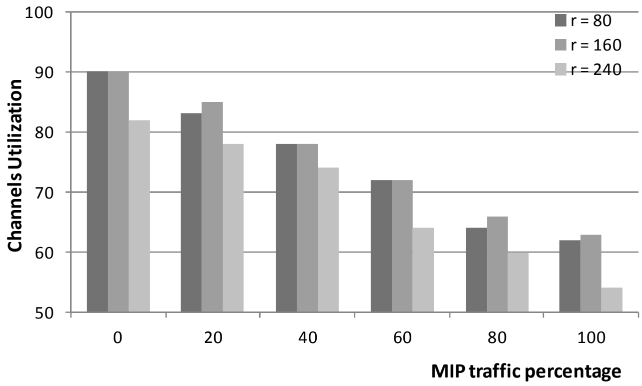

Fig. 4. Average channels utilization.

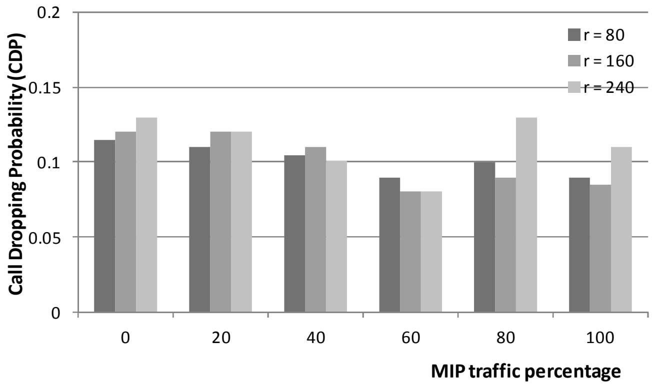

Fig. 5. Call Dropping Probability for different MIP traffic percentage and coverage radius.

The Call Dropping Probability (CDP) has been depicted in fig. 5: it does not heavily depend on MIP traffic percentage and its values belongs to the range [0.08, 0.14]. For lower values of *r*, the proposed distributed HMC scheme makes the CDP to be below 0.1.

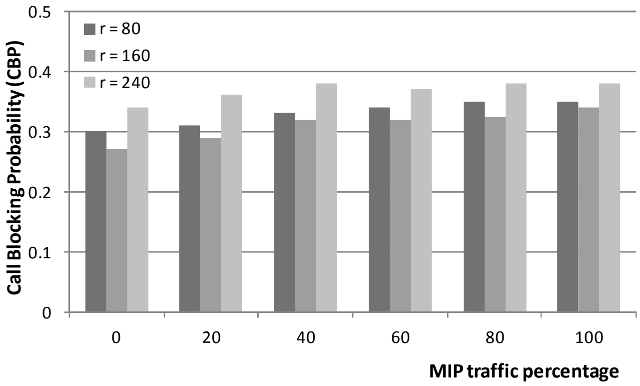

Fig. 6. Call Blocking Probability for different MIP traffic percentage and coverage radius.

For the Call Blocking Probability (CBP), fig. 6 shows how higher percentages of MIP traffic lead the system to have more passive reservation requests with the same channels availability, so the call admission control denies the access more frequently; for the same reason the trend is also increasing for larger *r*.

V. CONCLUSIONS

This paper proposed a new prediction algorithm scheme for wireless cellular networks, based on Hidden Markov Chains processes. It aims at the guarantee of service continuity in QoS networks and the idea is based on a distributed HMC approach, in order to predict user movements among a coverage system and to make possible an adequate reservation of passive resources. Many simulation campaigns have been led out in order to validate the proposed idea in terms of CDP, CBP and channel utilization and the obtained results have shown that acceptable accuracy is reachable with the proposed idea.

VI. 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] F. De Rango, P.Fazio, S.Marano, "Utility-based predictive services for adaptive wireless networks with mobile hosts", IEEE Transactions on Vehicular Technology, 2009.

[3] F. De Rango, P.Fazio, S.Marano, "Cell Stay Time Analysis under Random Way Point Mobility Model in WLAN Networks", IEEE Communication Letters, Vol.10, Issue 11, pp.763-765, Nov. 2006.

[4] F. De Rango, S.Marano, "An average degradation degree and ratio based rate adaptation algorithm for wireless mobile networks," in 15th International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC 2004), 5-8 September, Barcelona, 2004.

[5] 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.

[6] Chatzis, S.P., "Hidden Markov Models with Non elliptically Contoured State Densities", IEEE Transaction on Pattern Analysis and Machine Intelligence, Dec. 2010.

[7] 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

[8] L. Rabiner, "A Tutorial on Hidden Markov Models and selected Applications in speech Recognition", Proceedings of IEEE, 1989.

[9] Geng-Sheng Kuo; Po-Chang Ko, "Dynamic RSVP protocol," IEEE Communications Magazine, Volume 41, Issue 5, May 2003 Page(s): 130 – 135.

[10] M.Mirhakkak, N.Schult, and D.Thomson, "Dynamic Bandwidth management and adaptive applications for a variable bandwidth wireless environment," IEEE J.Select.Areas Comm., vol.22, pp.719-726, May 2004

[11] T.Zhang et al., "Local Predictive Resource Reservation for Handoff in Multimedia Wireless IP Networks," IEEE Journal on Selected Area in Communications, vol.19, no.10, Oct.2001,pp.1931-1941.

[12] T.Liu, P.Bahl, I.Chalmtac,"Mobility Modeling, Location Tracking, and Trajectory Prediction in Wireless ATM Networks," IEEE Journal on Selected Areas in Communication, vol.16, no.6, Aug.1998, pp.922-936

[13] J. A. Bilmes "A gentle tutorial of the EM algorithm and its application to Parameter Estimation for gaussian mixture and Hidden Markov Models", International Computer Science Institute Berkeley, 1998.

[14] I.F.Akyildiz, W.Wang, "The Predictive User Mobility Framework for Wireless Multimedia Networks," IEEE/ACM Transactions on Networking, vol.12, no.6, Dec.2004, pp.1021-1035.

[15] I.F.Akyildiz, W.Wang, "A Dynamic Location Management Scheme for Next-Generation Multiuser PCS Systems," IEEE Transaction on Wireless Communications, vol.1, no.1, Jan.2002, pp.178-189.

[16] L.-L.Lu, J.-L.C.Wu, W.-Y.Chen, "The study of handoff prediction schemes for resource reservation in mobvile multimedia wireless networks," International Journal of Communication Systems, vol.17, June 2004.

[17] Martinez, F.J., Cano, J.-C., Calafate, C.T., Manzoni, P., "CityMob: A Mobility Model Pattern Generator for VANETs", ICC Workshops 2008, pp. 370 – 374, Beijing.

[18] F. De Rango, P.Fazio, S.Marano, "Mobility prediction and resources reservation in WLAN networks under a 2D mobility model," in 64th Vehicular Technology Conference (VTC-2006 Fall), Montreal, 25-28 Sept., 2006.

[19] B. P. Vijay Kumar, P. Venkataram, "Prediction-based location management using multilayer neural networks", 2002.

[20] Micheal I. Jordan, "Graphical Models", Statistical Science, vol.19, pp.140-155, 2004.

[21] Sherif Akoush and Ahmed Sameh, "Mobile User Movement Prediction Using Bayesian Learning for Neural Networks", Proceeding of the 2007 International Conference on Wireless Communications and Mobile Computing, pp.191-196, 2007.

[22] Marichamy, P., Chakrabarti, S., Maskara, S.L., "Overview of handoff schemes in cellular mobile networks and their comparative performance evaluation", Vehicular Technology Conference, 1999, Amsterdam, Netherlands.