WPBR: Weekly Prediction based Bandwidth Reservation Scheme for Macrocellular Wireless Networks in Urban Areas

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Abstract—**One of the major challenges in the cellular networks is to guarantee the quality of service of the ongoing calls by prioritizing them over the new calls. An operative approach to prioritize the hand off calls over the new calls is by reserving bandwidth for the ongoing calls of mobile stations in the potential next cell that they may visit. Improving the prediction of potential next cell that a mobile station may visit will cause better bandwidth utilization. In this paper, we propose weekly prediction based bandwidth reservation scheme. The proposed scheme, WPBR, improves prediction by means of storing weekly movement probabilities of mobile station based on Markov modeling techniques. In order to decreasing the storage space that is needed for storing the mobile station's movement probabilities, we adopted a dynamic hashing approach. Simulation results show that the weekly prediction in the proposed scheme, significantly improves bandwidth utilization, and the adopted dynamic hashing approach caused the overhead of storage space to be acceptable.**

Index Terms*—*Macrocellular Wireless Networks, Bandwidth Reservation, Mobility Prediction, Markov Modeling Techniques, Dynamic Hashing.

I. INTRODUCTION

IN recent years there has been a rapid development in mobile and wireless cellular networks. One of the most major challenges in the mobile and wireless cellular networks is to efficiently utilize the bandwidth while the quality of service (QoS) of the ongoing calls should be guaranteed. However, due to user mobility, establishment and management of connections are very difficult.

A mobile and wireless cellular network consists of a lot of cells that serve a large number of mobile users with various mobility patterns and a number of applications. A cell involves a base station (BS) and a number of mobile stations (MSs). When an MS moves from the coverage of a cell into the coverage of another cell and there is an ongoing call, the call should be handed over from the prior cell to the new cell. This process is called hand off. If there is no available bandwidth to serve the hand off call in the new cell, then this call will not complete and will be dropped by the new BS. There are three elementary QoS parameters in the cellular networks: the hand off call dropping probability (CDP), the new call blocking probability (CBP) and the bandwidth utilization (BWU).

From the user point of view, dropping of an ongoing call is more undesirable than blocking of a new call. In the other word, ongoing calls must prioritized over new calls. In literature, several approaches have been proposed to give priorities to hand off calls [1]. One most common approach to prioritize hand off calls over new calls is by reserving channels for hand off calls. Schemes that utilize mentioned approach are classified as *channel reservation schemes* [1].

Reserving some bandwidth at each BS could only be utilized by hand off calls. Since any such reservation inevitably increases the CBP, and decreases the system's BWU, it is very important to make reservations as sparingly as possible. One astute way for the purpose of sparing reservation is to reserve bandwidth for each MS based on its predicted path through the cellular network. At first, the potential next cell that an MS may visit during its lifetime is predicted based on some information about the MS's mobility, and then, bandwidth reservation will be made only in the potential next cell that the mobile station may visit. In [1], schemes that utilize mobility prediction approach to reserve bandwidth are classified as *predictive mobile-oriented channel reservation schemes* (PMOCR).

The information that employed in the mobility prediction could be categorized into two types: current mobility parameters of MSs and observation histories of MSs. The schemes that using current mobility parameters like velocity, direction, angle or distance in their prediction, typically compute the probability of events occurring, depending on the values of these parameters. In [1], it mentioned that the key limitation of prediction by means of current mobility parameters is the requirement of positioning hardware.

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Another problem in these approaches is the overhead to obtain mobility parameters. However, the serious problem with these schemes is hidden behind the parameters and the mobility models that used in their predictions. The majority of these approaches utilize mobility models like random waypoint or its variants that fail to represent all or some of mobility characteristics (temporal and spatial dependency of velocity and geographic restrictions) that mentioned in [2]. But the predictions are unrealistic without representing mobility characteristics.

History-based schemes use historical mobility patterns of MSs to calculate their potential next cell. These schemes are based on a reasonable assumption that mobility of an MS shows some regularity in urban areas. In [1], it mentioned that the key limitation with all history-based schemes is the overhead to store and update observation histories for the MS's mobility.

There are two common approaches to work with observation histories: data mining techniques and markov modeling techniques. In data mining approach, user mobility patterns are mined from the history of mobile user trajectories. The MS's next movement is predicted by using mobility rules, which are extracted from the user mobility patterns. These trajectories are saved over time and the needed storage space will grow over time too. In markov modeling approach, potential next cell for an MS predicted based on historical mobility of the MS using Markov modeling. The Markovian mobility model defines distinct probabilities for movement from a given cell to each of its neighbors. Thus the needed space for storing movement probabilities in markov modeling approaches does not exceed a particular limit.

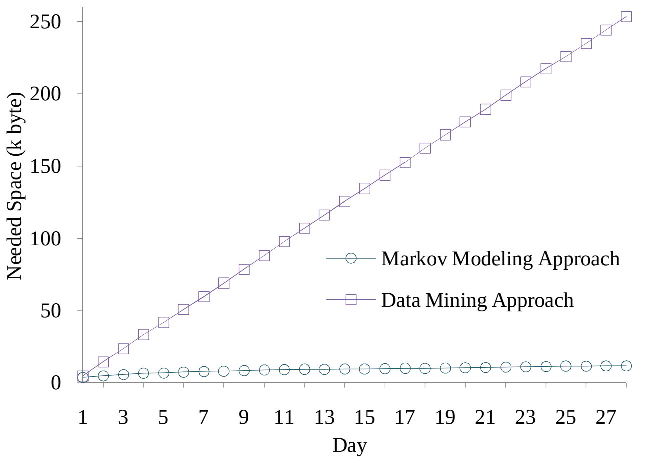

Figure 1.Comparison of needed storage space by data mining approach and markov modeling approach

In Figure 1 needed storage space of the markov modeling approach that suggested in [3], is compared to the data mining approach that explained in [4]. The comparison is done in a macrocellular wireless network with 25 cells and 95 mobile stations that move based on real time traces that have obtained through the reality mining project [7]. Our simulation results show that the needed space of data mining approach is extremely more than needed space of markov modeling approach. Thus the data mining approaches are not right choices for mobility prediction in the macrocellular wireless networks with a large number of mobile stations in urban area.

In this paper, we propose a predictive mobile-oriented bandwidth reservation scheme that improves prediction by means of storing weekly movement probabilities of MSs based on Markov modeling techniques. Also, we adopted a dynamic hashing approach in order to decreasing the storage space that is needed for storing the movement probabilities. Simulation results show that the weekly prediction in this novel strategy significantly improves bandwidth utilization, and the adopted dynamic hashing approach fairly overcomes the overhead of storage space.

The remainder of this paper is organized as follows: Section II gives an overview of related works. In section III the novel weekly-prediction-based bandwidth reservation (WPBR) strategy will be introduced. Section IV describes simulation environment and provides simulation results and discussions. Section V gives a plan for future works and concludes the paper.

II. Related Works

Many history-based mobility prediction schemes have been proposed to estimate the potential next cell that an MS may visit. In [3], a *dynamic location management* scheme have been introduced, in which potential next cell for an MS predicted based on historical mobility of the MS using Markov modeling. The Markovian mobility model defines distinct probabilities for movement from a given cell to each of its neighbors. These probabilities are stored in a matrix that called transition matrix. Each cell records movement probabilities based on the frequency of hand offs to its adjacent cells for each MS that is on a call inside the cell. Movement probabilities are updated at specified refresh intervals. Refreshing process may take place hourly, daily or more infrequently. The proposed algorithm for obtaining the movement probabilities is given as follows:

1) For every hand off to a neighbor cell, the hand off tally for that particular neighbor is incremented, or the cell is recorded as a neighbor if not previously seen.
2) On a cell refresh, each individual hand off tally is divided by the total number of hand offs to obtain the probability of moving to each cell.
3) Stored movement probabilities are smoothed using a simple exponentially weighted moving average as in (1).
4) Each hand off tally is reset to zero and the process is continued.

$$prob(c,i) = w\times prob(c,i-1) + (1-w)\times newProb(c). \qquad (1)$$

For each MS the probability of moving to cell c in the interval i obtained from (1), in which w is the smoothing factor. Each cell requires two hash maps, one to store the hand off frequencies that resulted in *newProb(c)*, and one to store the smoothed movement probabilities that used to predict potential next cell. MS's mobility patterns attain a steady state and are predictable after a series of repeated cell refreshes.

However, a single transition matrix for the whole day will cause unrealistic predictions [5]. In urban areas, a considerable number of MSs are moving from home to work every morning, and coming back from work to home in the afternoon. So, if an MS came back to home in the same path that has gone to work and refresh interval was greater than or equal to a day, a single transition matrix will give equal probability of occurrence for both of the movement paths (to work and to home) at any time of the day. In order to overcome this problem, the day is divided into eight fixed time slots (00:00-6:00, 6:00-8:00, 8:00-10:00, 10:00-12:00, 12:00-14:00, 14:00-16:00, 16:00-18:00, 18:00-24:00). Individual transition matrixes are created and maintained for each of the eight time slots [5]. This approach will cause more realistic mobility prediction, but on the other hand it increases the storage space that is needed for storing the movement probabilities.

III. Weekly Prediction based Bandwidth Reservation Scheme

In this section, proposed radio resource management scheme would be introduced. When MS *i* moves into the coverage of cell *c* in time slot *t* of day *d* and there is an ongoing call, a hand over request will be sent to call admission control module of cell *c*. Then call admission control module gets the available radio resources from radio resource management module. If there was not enough resource, the call request will be rejected. If there was enough resource, call admission control module will allocate the resources to MS *i*. Subsequently call admission control module will get the potential next cell from prediction module and will send a bandwidth reservation request to the resource reservation module of potential next cell, and then resource reservation module reserves requested bandwidth if possible. The structure of proposed radio resource management scheme has been depicted in Figure 2.

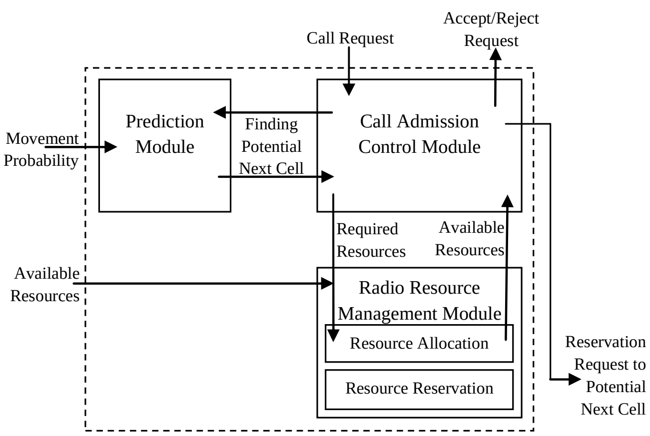

Figure 2. The structure of proposed radio resource management scheme

In Table I, the main steps of the call admission control module are described using pseudo code. In the rest of this section, the structure and the action of prediction module would be introduced.

TABLE I. Pseudo Code Describing The Call Admission Control Module

```
//method gets MS id,i , and required radio resource, rrr, as input
arr = available radio resource from radio resource management module
if(rrr<arr)
    accept the request
    nCell = get the potential next cell from prediction module
    send reservation request to nCell
else
    reject the request
```

A. Weekly Behavior Similarity

In [6], authors have tried to expand the comprehending of pragmatic user behavior in macrocellular wireless networks, utilizing real time traces. The traces have obtained through the reality mining project [7]. We use their traces in this paper too. In [6], the parameter pr_1 defined as in (2):

$$pr_1 = \frac{Number\ of\ newly\ visited\ cells}{Total\ visits}. \tag{2}$$

The ratio pr_1 indicates that to what extent the user mobility behavior is predictable. The swing in value pr_1 from the day i to the day i+7 of each week is seen to follow a periodic pattern. Comparable weekly patterns suggest repetitive patterns in user movements. It seems that mobility pattern of MSs is repetitive with a period equal to a week.

Now, we introduce another parameter to indicate to what extent the user mobility behavior is similar to its mobility behavior in the previous days. Behavior similarity of MS *i* in the day *n* to its behavior in the day *n-j* that indicated by $S_i(n, n-j)$ defined as in (4):

$$N_i(c_k, n) = Number\ of\ times\ that\ MS\ i\ visits\ cell\ k\ in\ day\ n. \tag{3}$$

$$S_i(n, n-j) = \frac{\sum_{for\ all\ k} min(N_i(c_k,n), N_i(c_k, n-j))}{\sum_{for\ all\ k} N_i(c_k,n)}. \tag{4}$$

Also, behavior similarity of all MSs in the day *n* to their behaviors in the day *n-j* that indicated by $\bar{S}(n, n-j)$ defined as mean of similarity ratios of all the MSs in the network as in (5):

$$\bar{S}(n, n-j) = \frac{\sum_{for\ all\ i} S_i(n,n-j)}{number\ of\ MSs}. \tag{5}$$

A plot of $\bar{S}(28, 28-j)$ for *0≤j<28* is given in Figure 3. It is obvious that $S_i(n, n)$=1 and so $\bar{S}(n, n)$=1.

$\bar{S}(n, n-j)$ could be used as a parameter to indicate that to what extent the mobility behavior in the network is similar to the previous days. Figure 3 illustrates that in the macrocellular wireless networks, the mobility behavior in the day *i* is similar to the mobility behavior in the day *i-7*. Therefore, it seems that mobility prediction based on weekly observations is more pragmatic than mobility prediction based on daily observations.

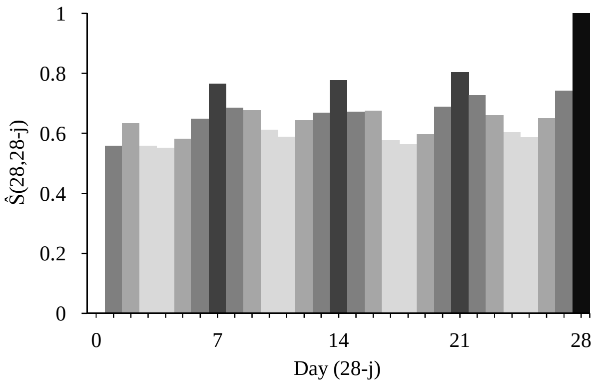

Figure 3. Behavior similarity of MSs in day 28 to their behavior in the previous days

Similarity ratio could be defined for time slots either. Assume $N_i(c_k, n, t)$ indicates the number of times that MS i visits cell k in time slot t of day n. Behavior similarity of MS *i* in the time slot *t* of day *n*, to its behavior in the time slot *t'* of day *n-j* that indicated by $TS_i(n, t; n-j, t')$ defined as in (6):

$$TS_i(n, t; n-j, t') = \frac{\sum_{for\ all\ k} min(N_i(c_k,n,t), N_i(c_k,n-j,t'))}{\sum_{for\ all\ k} N_i(c_k,n,t)}. \qquad (6)$$

Behavior similarity of all MSs in the time slot *t* of day *n* to their behaviors in the time slot *t'* of day *n-j* that indicated by $\overline{TS}(n, t; n-j, t')$ defined as mean of similarity ratios of all the MSs in the network as in (7):

$$\overline{TS}(n, t;\ n-j, t') = \frac{\sum_{for\ all\ i} TS_i(n,t;n-j,t')}{number\ of\ MSs}. \qquad (7)$$

A plot of $\overline{TS}(28{,}10; 28-j, t')$ for $14 \le j < 28$ and $0 \le t' \le 10$ is given in Figure 4. It is obvious that $\mathrm{TS_i(n, t; n, t)}$=1 and so $\overline{\mathrm{TS}}(\mathrm{n, t; n, t})$=1.

The time slot similarity ratio, $\overline{\mathrm{TS}}(\mathrm{n, t; n-j, t'})$, could be used as a parameter to indicate that to what extent the mobility behavior in the network is similar to the previous time slots. Figure 4 illustrates that in the macrocellular wireless networks, the mobility behavior in the time slot *t* of day *d* is similar to the mobility behavior in the time slot *t* of day *d-(x*7)* that $x \in \{1, 2, 3, \ldots\}$.

B. Weekly Prediction

And now, we introduce our weekly predictive bandwidth reservation strategy. In order to predict movement of each MS, the week is divided into 56 fixed time slots (each day is divided into eight time slots as explained in [5]). Individual transition matrixes are created and maintained for each of the 56 time slots during the week. For MS *i* the probability of moving to cell *c* in time slot *t* of the day *d* indicated by $p_i(c, t, d)$ which obtained through the frequency of hand offs to cell *c* during time slot *t* of day *d*. Movement probabilities will be updated using (8) at the end of each time slot. The transition matrix for MS *i* in time slot *t* of day *d* indicated by $M(i, t, d)$.

$$P_i(c, t, d) = w \times P_i(c, t, d) + (1-w) \times newProb(c). \qquad (8)$$

When MS *i* moves into the coverage of new cell in time slot *t* of day *d* and there is an ongoing call, *prediction module* of the cell detects the corresponding transition matrix and then, searches the matrix for maximum transition probability

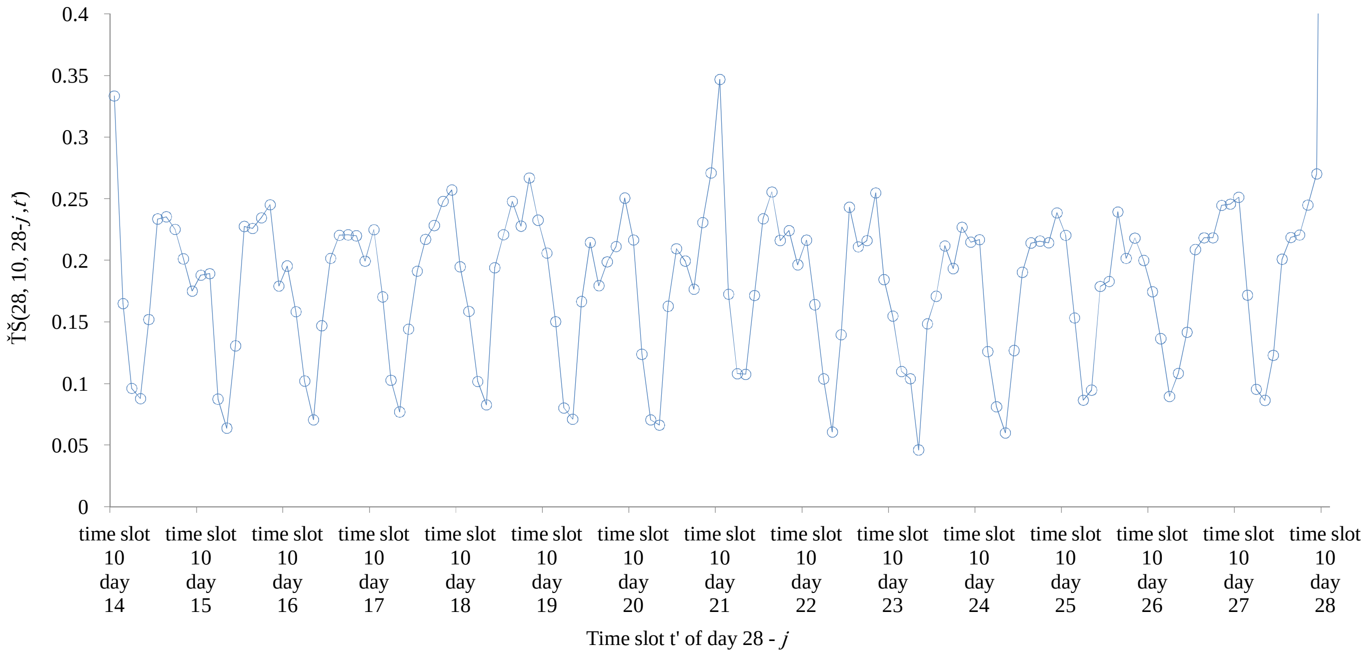

Figure 4. Behavior similarity of MSs in time slot 10 of day 28 to their behavior in the previous time slots

(p_i^{max}).

$$p_i^{max} = max_{for\ each\ adjacent\ cell\ c}\{p_i(c,t,d)\}. \tag{9}$$

As it mentioned, time slots are fixed and the MS behavior fluctuates from day to day. Hence a movement might be captured in the adjacent time slots which may result in incorrect predictions. It is difficult to use variable time slots and this problem will not be solved even if variable time slots be used.

In order to overcome this problem, the prediction could be made with the aid of transition matrix of the adjacent time slots. The mobility behavior of MSs in time slot *t* of day d is moderately similar to their mobility behavior in time slot *t-1*and *t+1*of day d of the previous weeks as it could be seen in Figure 4. Thus, in order to resolve the problem of MS's behavior fluctuation, prediction module could make predictions based on the transition matrixes $M(i,t-1,d)$, $M(i,t,d)$ and$M(i,t+1,d)$.

If p_i^{max} was greater than or equal to a minimum threshold p_{min}, the bandwidth reservation request will be sent to the cell that maximizes (9). Otherwise, if $p_i^{max}$was less than p_{min}, the prediction will be made based on $\bar{p}_i^{max}$ that obtained from (10). In the other word, if p_i^{max} was less than p_{min}, the bandwidth reservation request will be sent to the cell that maximizes (10).

$$\bar{p}_i^{max} = \underset{for\ each\ adjacent\ cell\ c}{max}\{q \times p_i(c,t,d) +$$

$$\frac{1-q}{2} \times p_i(c,t-1,d) + \frac{1-q}{2} \times p_i(c,t+1,d)\}. \tag{10}$$

The algorithm effectiveness affected by choosing appropriate value for p_{min}. Choosing a high value for p_{min} results in smoothed prediction, but also, increases the number of accesses to the transition matrixes from 1 to 3. For each adjacent cell *c*, the probability $p_i(c,t,d)$ will be equal to 0, and so, p_i^{max} will be equal to 0 until the first movement is captured in the time slot *t* in the day *d*. After capturing the first movement in the time slot *t* of day d, $\sum_{\forall c} p_i(c,t,d)$ will be equal to 1. Hence, if the number of adjacent cells is *n*, the minimum value for p_i^{max} will be $1/_n$. Thus, p_{min} should be greater than or equal to $1/_n$.Assuming the number of adjacent cells to be 6, p_{min} should be greater than or equal to $0.1\bar{6}$. The value of p_{min} was chosen to be 0.2 to make more accurate predictions.

The weighting factor q in (10) indicates that to what extent $\bar{p}_i^{max}$is affected by adjacent time slots. If any movement still not captured, q should be equal to 0 in that time slot. Otherwise, it should be greater than 0. So, q obtained from (11):

$$q = q' \times \sum_{foreachadjacentcellc} p_i(c,t,d). \tag{11}$$

It seems that q' should be greater than or equal to $0.\bar{3}$. If q' was less than $0.\bar{3}$, the current time slot movement probabilities is less effective than adjacent time slot movement probabilities in calculating $\bar{p}_i^{max}$, and it does not makes sense. The value of q' must be proportionate to behavior similarity of MSs to their behavior in time slots *t*, *t-1* and *t+1*. Thus, there is a direct correlation between q' and time slot similarity ratio ($\overline{TS}$). The parameter q' could be obtained from (13) for each time slot *t*.

$$q'_{(j)} = \frac{\overline{TS}(n,t;n-(j\times7),t)}{\overline{TS}(n,t;n-(j\times7),t-1)+\overline{TS}(n,t;n-(j\times7),t)+\overline{TS}(n,t;n-(j\times7),t+1)}. \tag{12}$$

$$q' = \frac{\sum_{j=1}^{[n/_7]}\left(q'_{(j)}\right)}{[n/_7]}. \tag{13}$$

In (12) the parameter $\overline{TS}$ is the time slot similarity ratio and $q'_{(j)}$ indicates the correlation of mobility behavior in time slot *t* to mobility behavior in time slot *t* of *j* weeks ago.q' obtained from averaging out the values of $q'_{(j)}$ for j={1, 2, …, $[n/_7]$}. The parameter q' could be obtained at the beginning of each time slot or could be obtained for all time slots after an initial period (about a month). Based on reality mining traces that used in this article, the value of q' was chosen to be between 0.4 and 0.5 to make more accurate predictions.

TABLE II. PSEUDO CODE DESCRIBING THE PREDICTION MODULE

//method gets *i*, *t* and *d* as input
$\boldsymbol{p_{min}}$ = 0.2
σ = 0
$\boldsymbol{p_i^{max}}$ = 0
$\boldsymbol{c_i^{max}}$ = null
while(there is another adjacent cell)
    c = next adjacent cell
    σ += $\boldsymbol{p_i(c,t,d)}$
    if($\boldsymbol{p_i(c,t,d)}$>$\boldsymbol{p_i^{max}}$)
        $\boldsymbol{p_i^{max} = p_i(c,t,d)}$
        $\boldsymbol{c_i^{max}}$ = c
if($\boldsymbol{p_i^{max}}$>$\boldsymbol{p_{min}}$)
    return $\boldsymbol{c_i^{max}}$
else
    $\boldsymbol{\bar{p}_i^{max}}$ = 0, $\boldsymbol{q}$ = 0.5∗σ
    while(there is another adjacent cell)
        c = next adjacent cell
        p = $\boldsymbol{q \times p_i(c,t,d) + \frac{1-q}{2}\left(p_i(c,t-1,d) + p_i(c,t+1,d)\right)}$
        if(p>$\boldsymbol{\bar{p}_i^{max}}$)
            $\boldsymbol{\bar{p}_i^{max}}$ = p
            $\boldsymbol{c_i^{max}}$ = c
if($\boldsymbol{\bar{p}_i^{max}}$= =0)
    $\boldsymbol{\overleftarrow{\sigma}}$ = 0
    $\boldsymbol{\overleftarrow{p}_i^{max}}$ = 0
    while(there is another adjacent cell)
        c = next adjacent cell
        $\boldsymbol{\overleftarrow{\sigma}}$ += $\boldsymbol{p_i(c,t,d-1)}$
        if($\boldsymbol{p_i(c,t,d)}$>$\boldsymbol{\overleftarrow{p}_i^{max}}$)
            $\boldsymbol{\overleftarrow{p}_i^{max} = p_i(c,t,d-1)}$
            $\boldsymbol{c_i^{max}}$ = c
return $\boldsymbol{c_i^{max}}$

When a BS attaches to the cellular network, it has no background information about the mobility patterns. Hence any prediction and reservation will not be made in the initial period. The mobility pattern of MSs in day d, is moderately similar to the mobility pattern in day $d-1$ and day $d+1$ of the previous weeks as it could be seen in Figure 3. So, in order to improve prediction in the initial period, prediction module could make prediction based on the transition matrix for the MS in time slot *t* of day $d-1$, $M(i,t,d-1)$.

The prediction module of each cell gets *i*, *t* and *d* as inputs that indicate the MS id, the time slot and the day of week respectively. At the end, prediction module returns the potential next cell that MS *i* may visit, and subsequently bandwidth will be reserved in the predicted cell. In Table II, the main steps of the prediction module are described using pseudo code.

C. Storing Movement Probabilities

Weekly prediction needs to store and update transition matrixes weekly that require more storage space. In weekly prediction, for each MS, there are 56 time slots whereas in daily prediction 8 time slots should be traced for each MS. It seems that required storage space for weekly prediction is 7 times the required storage space for daily prediction. However, in practice, some time slots will never capture any movements. Simulation results show that in actual traces, required storage space for weekly prediction is 3 to 4 times the required storage space for daily prediction. This ratio could be decreased to 2.5 using dynamic hashing approach. Decreasing the required storage space in macrocellular wireless networks is crucial due to existence of a large number of MSs.

In order to storing movement probabilities, hashing has been suggested in [3]. The hash function maps MS id into the stored probabilities. When an MS, for the first time, moves into the coverage of new cell, all the space that is needed for movement probabilities will be allocated to it. However, as it mentioned, some of the time slots will never capture any probabilities. In this work, a dynamic hashing approach has been introduced to allocate just the required storage space to an MS.

Dynamic hashing promises the flexibility of needed storage space while preserving the fast access times expected from hashing [8]. Dynamic hashing is a type of hashing which treats a hash as a bit string. The hash function $h(k)$ returns a unique binary number that its first *b* bits will be used to figure out where they will go in the hash table. Additionally, *b* is the smallest number such that the first *b* bits could be the same for utmost b_{max} keys, that b_{max} is the bucket size.

In this article, in order to simplify hashing, the binary format of keys is used as the bit string. The transition matrix of MS *i* in time slot *t* of day *d* indicated by $M(i,t,d)$. So the key may consist of 3 fields, MS id, time slot and the day. Now the question is, how first *b* bits should be structured and what fields must first *b* bits consist of?

The plot of time slot similarity that had been depicted in Figure 4 has been shown again for the last week in Figure 5. In this sample, similarity of last week time slots to the reference point, time slot 10 of day 28, has been depicted. Square shape data points indicate the most similar time slots of the most dissimilar days to the reference point time slot in the last week. As it mentioned, the most similar time slot in previous days to a reference point time slot is the same time slot in previous days. Triangle shape data point indicates the most dissimilar time slot of the most similar day to the reference point time slot in the last week. As it mentioned, the most similar day in

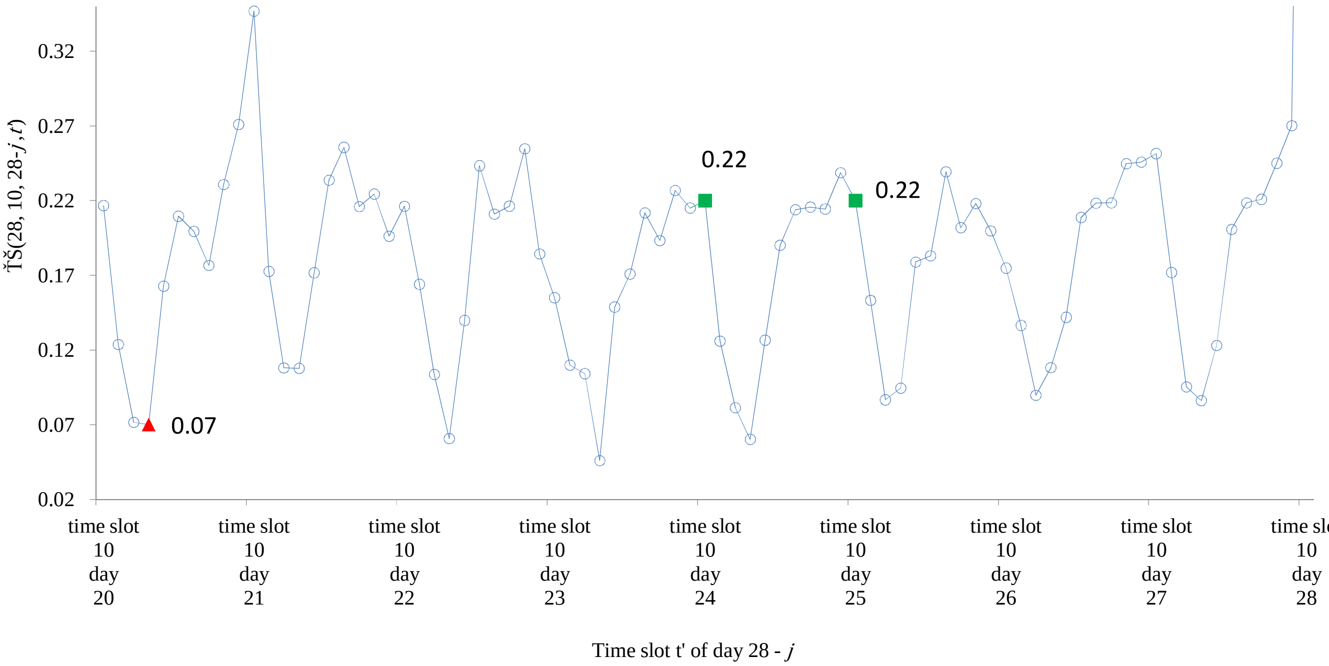

Figure 5. Behavior similarity of MSs in time slot 10 of day 28 to their behavior in the last week time slots

previous weeks to a reference point day is the same day in previous weeks. As it could be seen in Figure 5, square shape data points are more similar to the reference point time slot than triangle shape data point. In the other word, mobility behavior of MSs in different time slots of a day varies more than mobility behavior of MSs in the same time slots of different days. Thus, the number of new entries that captured in different time slots is more than new entries that captured in different days. Hence hash could be structured as following:

1) First b bits could consist of MS id, i.
2) First b bits could consist of some of the most significant bits of time slot, t.
3) If first b bits were same for more than b_{max} keys, first b bits shall extend. The extension shall done to the remaining bits of time slot and then encompass the day bits, d.

At first, the set of i and 2 most significant bits of t could be used in construction of the hash table. For example, the entry $M(6,5,3)$ will go into the index 11010 of hash table. In some cells, this set could be adequate to construct the hash table. If there was an entry that causes the bucket size exceeds b_{max}, the hash table size will be doubled.

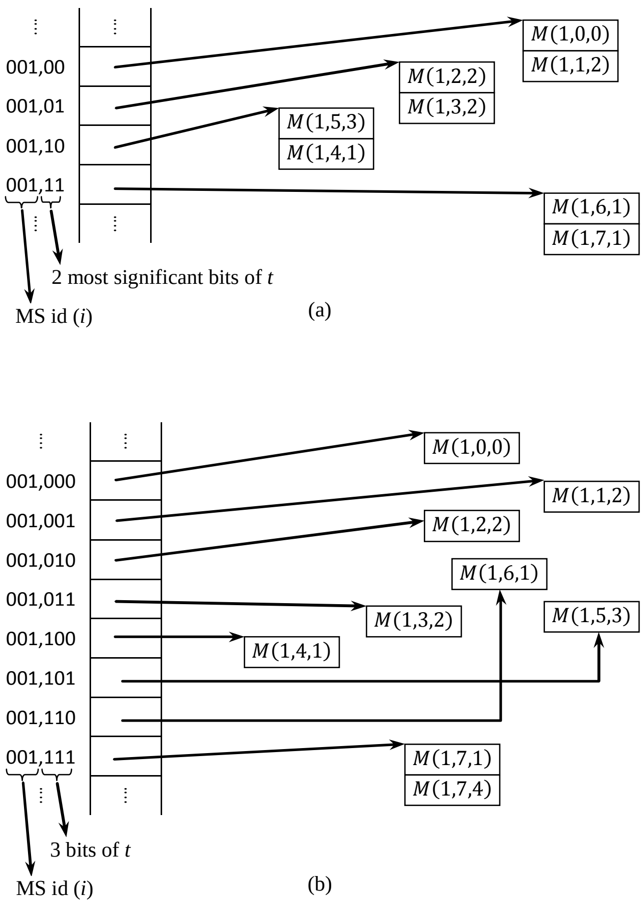

Figure 6. An example of adopted dynamic hashing approach, (a) before entering $\mathbf{M(1,7,4)}$, (b) after entering $\mathbf{M(1,7,4)}$

An example of dynamic hashing approach has been depicted in Figure 6. It has been assumed that for this particular example, the bucket size is 2. Before entering $M(1,7,4)$, the set of i and 2 most significant bits of t is adequate to construct the hash table as it has been shown in Figure 6(a). In order to enter $M(1,7,4)$, the hash table should be doubled as in Figure 6(b). Likewise, other bits of the key could be included in the set and the hash table size could increase.

Simulation results show that for the majority of cells, the undesirable increase in the hash table size will persist to a certain extent, and the dynamic hashing approach moderately overcomes the overhead of storage space. Moreover, dynamic hashing causes storage space to increase imperceptibly. Also it is possible to decrease the storage space by deleting transition matrixes that will not be used any more. However, opportunity to decrease storage space is not investigated here.

IV. Simulation And Results

In order to evaluate the performance of proposed weekly-prediction-based bandwidth reservation (WPBR) strategy, the daily prediction based bandwidth reservation (DPBR) scheme has been implemented and simulated for comparison. The algorithms of daily prediction that described in section II and weekly prediction that described in section III have been implemented using Java.

A. Simulation Model

The data set that have been used in this study, developed by researchers at MIT Media Laboratory, and came from Nokia 6600 phones programmed to automatically run the ContextLog application as a background process at all times [7]. These real time mobility traces have been mapped into a macrocellular network with 25 hexagonal cells that each cell has 6 adjacent cells. Table III summarizes the various simulation parameters whose values were empirically chosen to represent the most realistic scenario for the simulation. Each simulation was carried out for 28 days of real time traces in the macrocellular network. It is assumed that the arrival rate of new calls is a Poisson distribution with a mean arrival value of 0.5.

TABLE III. Simulation Parameters

Parameter	Value	Description of parameter
N_C	25	Number of cells simulated
N_{ms} [a]	95	Number of mobile stations in system
B_c	30Mbps	Maximum bandwidth capacity of a cell
B_{req}	3Mbps	Average bandwidth requirement for a call
$\bar{C}_r$	0.5req/s	Average connection arrival rate
$\bar{C}_d$	235 s	Average call duration
w	0.5	The weighting factor that used in (1)
q	0.5	The weighting factor that used in (8)
p_{min}	0.2	The threshold that indicates which time slots should participate in prediction

a. This number came from number of MSs that have been traced in reality mining project [7]

B. Experimental Results

Figure 7 compares the bandwidth utilization of the WPBR strategy with the DPBR scheme for 28 days of simulation and average connection arrival rate 0.5. There is no background information about the mobility patterns in the first day, hence no prediction will made and bandwidth utilization values are high for both schemes. As time passed, mobility information is gradually gathered. Prediction and the respective bandwidth reservation will cause bandwidth utilization value to decrease. For the DPBR scheme, bandwidth utilization values decrease to an extent and after that leveled off at about 0.4. The subsequent negligible fluctuation in the bandwidth utilization values of the DPBR scheme has arisen from alteration in the behavior of MSs. For the WPBR scheme, bandwidth utilization values decrease for an initial period (about a week) and then increase with improvement in the prediction. The accurate and sparing prediction caused the WPBR scheme to gain higher bandwidth utilization.

Figure 8 compares the new call blocking probability of the WPBR strategy with the DPBR scheme for average connection arrival rate 0.5. March of progress in CBP is similar to what expressed about bandwidth utilization before. For the WPBR scheme, CBP increases for an initial period (about a week) and then decreases with improvement in the prediction and cause the WPBR scheme to gain lower CBP.

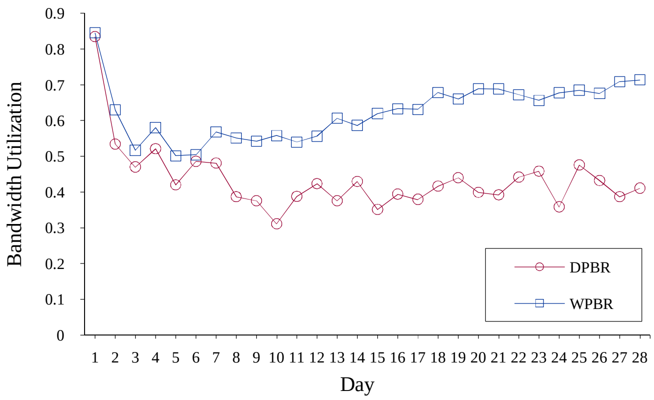

Figure 7. Comparison of bandwidth utilization by the two schemes for average connection arrival rate 0.5

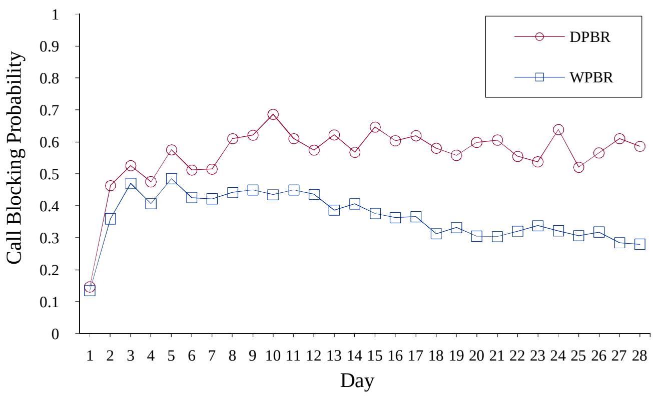

Figure 8. Comparison of new call blocking probability by the two schemes for average connection arrival rate 0.5

Figure 9 compares the hand off call dropping probability of the WPBR strategy with the DPBR scheme for average connection arrival rate 0.5. For the DPBR scheme, CDP decrease to an extent and after that leveled off at about 0.15×10^{-2}. For the WPBR scheme, decrease in CDP for an initial period is less than decrease in CDP for the DPBR. The trend line of the WPBR scheme shows that CDP is dwindling by the time. . As the WPBR scheme distinguishes between days of the week, its CDP fluctuates in the course of a week. The weekly fluctuation in the CDP of the WPBR scheme shows that the behavior of MSs is more predictable in some days of the week. For example the MS behavior on workdays could be more predictable than weekends.

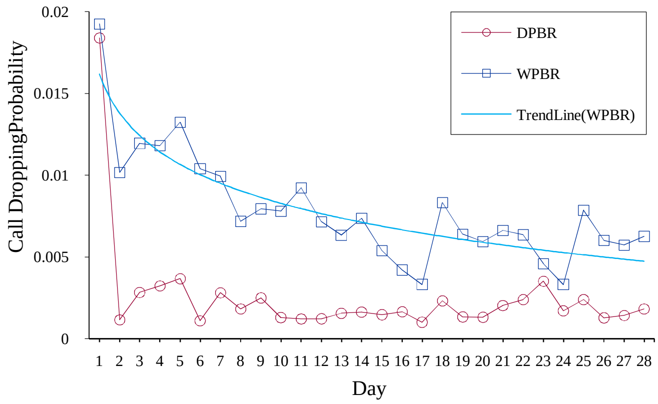

Figure 9.Comparison of hand off call dropping probability by the two schemes for average connection arrival rate 0.5

From the MS's point of view, the objective is to minimize CBP and specially CDP in order to improve the performance of the network. Another objective, from the service provider's perspective is to decrease the cost by increasing BWU of the network. In order to make a fair balance between both user satisfaction and service provider satisfaction, one should consider the cost/performance ratio (Z) which is defined in [9] as (14) where *r* is the penalty factor used to reflect the effect of the hand off dropping over the new call blocking. A penalty of 5–20 times is commonly recommended [9].The design goals of a call admission control scheme are increasing the performance and decreasing the cost, which means minimizing Z.

$$Z = \frac{cost}{performance} = \frac{r \times CDP + CBP}{BWU}. \quad (14)$$

Figure 10 depicts Z versus *r* on the day 28 of simulation. It shows that the proposed WPBR scheme, for penalty of 5–20 times, has a lower Z value than DPBR scheme.

Figure 11 compares the required storage space of the WPBR strategy with the DPBR scheme for 28 days of simulation. It seemed that required storage space for the WPBR was 7 times the required storage space for the DPBR. But simulation results show that in actual traces, required storage space for the WPBR is approximately 2.5 times the required storage space for the DPBR. So, the adopted dynamic hashing approach moderately obviates the overhead of storage space.

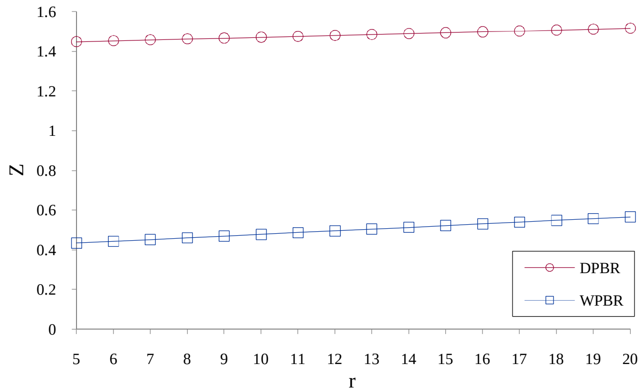

Figure 10. Z versus r on the day 28 of simulation

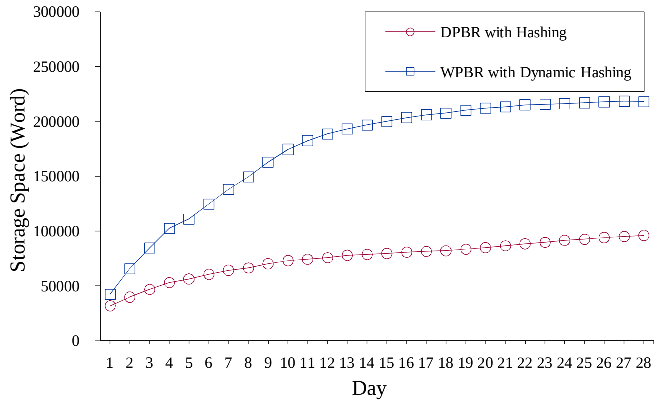

Figure 11. Comparison of used storage space by the two schemes

V. CONCLUSIONS

A weekly predictive mobile-oriented bandwidth reservation strategy has been proposed that improves prediction by weekly storing movement probabilities based on Markov modeling techniques. And also, a dynamic hashing approach has been adopted to decrease the required storage space. Simulation results show that the weekly prediction in this novel strategy significantly improves bandwidth utilization, and the adopted dynamic hashing approach moderately overcomes the overhead of storage space.

Unfortunately, the cell residence time of mobile stations is not included in the bandwidth reservation strategy. When a mobile station moves into the coverage of new cell and there is an ongoing call, bandwidth will be reserved in the potential next cell and the cell residence time of the mobile station has not been taken into account. This topic is an interesting area for further researches.

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