Wireless Subscriber Mobility Management using Adaptive Individual Location Areas for PCS Systems

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Abstract **— We consider a new mobility management scheme – the Adaptive Location Area Tracking Scheme, in which each mobile performs a location registration as it crosses the boundary of its current *personal location area* and is assigned a new location area. The size and shape of the new location area depend on the mobile's mobility and call characteristics in its previous location area. The objective is to minimize the combined average signaling cost of both paging and registration activities for each individual mobile user.**

We model the mobility and incoming call traffic of an individual mobile user using Brownian motion with drift process and Poisson arrival process. Under the assumption of a one-dimensional cellular network environment, we investigate the effects of user mobility parameters such as average movement speed, *location uncertainty* and mean call arrival rate on the size and shape of individual location areas. This study reveals that, besides size, the shape of location areas also plays an important role in signaling cost reduction. Performance analysis shows that this scheme offers a cost reduction up to 50% as compared to a previously proposed scheme.

1 Introduction

As current wireless networks evolve toward personal communications systems, the rapidly growing subscriber density stresses limited network resources. As users move, the system must be informed so that calls may be routed to them. From the network perspective, however, user movement from one location area to another also sets in motion a series of costly network events which can include moving user databases and re-authentication [10]. Efficient mobility management – keeping track mobile unit location – is therefore of paramount importance from both a quality of service and a network signaling resource allocation perspective.

A location area (LA) is a group of locations (cells) where the user is currently likely to reside. If the user moves from that area it must register its movement with the system (*registration*) or calls cannot be routed to it. Such registration can be costly [10] and making the LA very large to reduce registration drives up the cost of searching for the specific user location to route an incoming call (*paging*). Current wireless systems such as GSM use a fixed LA strategy for mobility management where the same LAs are used for everyone. The major problems with this strategy are that the fixed LA chosen based on the aggregate mobility and call statistics is *not optimal individually*, and that the scheme *cannot adapt* to the changing mobility and call characteristics.

Dynamic Location Area Management Scheme [1, 2] proposed previously intended to solve those problems, which introduced an *Individual LA* concept. Rather than using fixed LAs for all users, this scheme uses a different LA for a different user. The performance of this scheme is in general significantly better than the fixed LA scheme. In the study of the scheme, however, the traditional fluid flow model [9] was used to model the mobility of an individual user. Because the fluid flow mobility model is purely based on the average mobility information of all users, it cannot capture the motion characteristics of a particular mobile user. Moreover, most previous work in mobility management discussed only the sizing problem of LAs — how many locations should be put into an LA. However, the problem of *LA shape* with respect to different movement and call patterns had not been studied.

Here, we propose a new scheme, the Adaptive Location Area Tracking Scheme, which improves the Dynamic LA Scheme in the following two ways: (1) we formulate the location tracking problem using improved individual mobility modeling techniques and registration rate calculation methods, and (2) investigate the influence of the directional motion and motion uncertainty of an individual user on the size and shape of its LAs.

A Brownian motion with drift model was chosen to model mobility of an individual user. This model is analytically tractable and reasonably versatile. Assuming a one dimensional cellular system, we find the optimum position and size of the LA relative the user's last known position. We found that LA shape (placement relative this last known position in one dimensional case) plays an important role in signaling cost reduction.

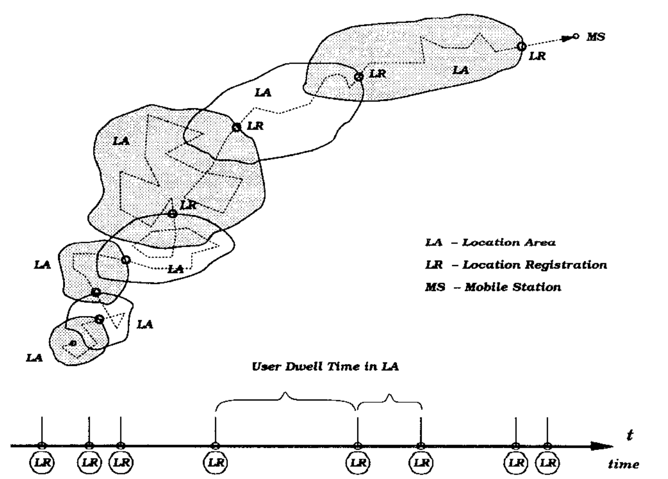

Figure 1: *Illustration of Adaptive Location Area Tracking Scheme*

Performance analysis shows that this scheme can improve the tracking performance by up to a factor of 2 compared to the previously-proposed Dynamic Location Area Management Scheme [1, 2]. Unfortunately, this approach is intractable for two dimensions [12]. For the two dimensional cellular system environment, we solve the mobility tracking problem by formulating the problem differently [6, 7].

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2 Problem Formulation

The Adaptive Location Area Tracking Scheme is a scheme which chooses the LA on a per-user basis. Upon each location registration (LR) at the boundary crossing of the personal LA, a new LA is assigned to a user and the new LA is determined according to the user's mobility and call characteristics in its previous LA. Figure 1 illustrates the basic idea of the scheme. The goal is to minimize the combined average signaling cost due to both paging and registration for each individual mobile user, such that the overall system-wide signaling cost for location tracking can be minimized.

The signaling cost for registration depends on the average registration rate of a user which is inversely proportional to the mean user dwell time within the LA. While the cost for paging is proportional to the mean rate of incoming call arrivals and the number of cells inside the LA. To reduce the overall cost, registration procedures require the LA to expand while paging procedures want the LA to shrink. Those conflicting requirements form an LA optimization problem.

2.1 Mobility Modeling for Individual User

Mobility modeling for an individual user requires a model that describes the time-varying motion of an individual and has motion parameters readily available for analysis. A basic mobility characteristic is the increase in user *location uncertainty* with time since the last user-network interaction. Brownian motion with drift model [11,12] nicely fits this description. The one dimensional Brownian motion with drift process starting at position x_0 at time t_0 can be described as:

$$p_x(x|x_0,t) = \frac{1}{\sqrt{2\pi\mathcal{D}(t-t_0)}} \exp\left\{-\frac{[x-x_0-v(t-t_0)]^2}{2\mathcal{D}(t-t_0)}\right\}, \quad t \geq t_0 \tag{1}$$

where $\mathcal{D}$ is the diffusion constant (length^2/time) is parameter which represents the *location uncertainty* of the motion, and v the drift velocity (length/time) which represents the average velocity of a moving user.

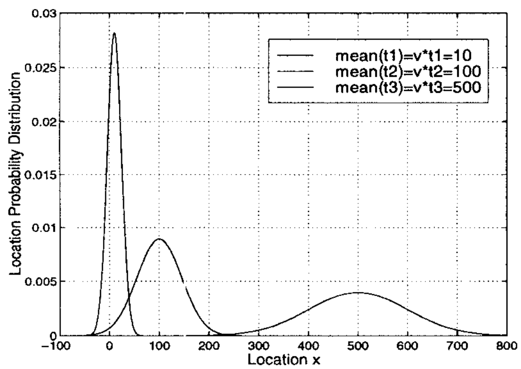


Figure 2: *The time-varying pdf of a Brownian motion with drift process ($\mathcal{D} = 200$, $v = 10$) at three time instants: $t_1 < t_2 < t_3$.*

High $\mathcal{D}$ and v indicate a very active movement, while low $\mathcal{D}$ and v suggest very little change in the location as time elapses. However, it is worth noting that large v and small $\mathcal{D}$ imply *low location uncertainty* – even though the user might move rapidly.

The **Mean First Passage Time (MFPT)** of a process is defined as the average time required to first breach specified boundaries containing the starting point of the process [11]. MFPT represents exactly the mean dwell time of a motion process in a bounded area.

Let the boundaries of the one dimensional LA be given as B_1 and B_2 with $B_1 \leq x_0 \leq B_2$. The MFPT for a Brownian motion with drift process starting at x_0 is derived in [4] as:

$$T(x_0, B_1, B_2) = \frac{1}{v}\left\{\frac{1-e^{-2v(x_0-B_1)/\mathcal{D}}}{1-e^{-2v(B_2-B_1)/\mathcal{D}}}(B_2-B_1)-(x_0-B_1)\right\} \tag{2}$$

Known MFPT as the average time between any two registration events, the average registration rate can be determined as inversely proportional to the MFPT.

2.2 Cost Structure

The overall average signaling cost [signaling units/unit time/subscriber] is defined as the sum of average paging cost C_p and average location registration cost C_r since paging and registration are two independent events in this scheme [1,2,4].

Assume the incoming call arrivals for a user are Poisson of intensity λ_p. We define the average cost of paging as:

$$C_p = S_p\lambda_p \times N\left\{\frac{L_{LA}}{L_c}\right\} \quad \text{[signaling units/unit time]} \tag{3}$$

where S_p is the paging cost coefficient [signaling units/paging event]; $L_{LA} = B_2 - B_1$ is the LA size; L_c is the cell size, assuming all the cells in the system are identical. $N\{\cdot\}$ is defined as a counting function that counts every cell contained fully or partially in the LA region [B_1, B_2]. For simplicity, we approximate $N\{\cdot\}$ as: $N\left\{\frac{L_{LA}}{L_c}\right\} \approx \frac{L_{LA}}{L_c}$, assuming $L_{LA} \gg L_c$.
The average cost of location registration is defined as:

$$C_r = S_r\frac{1}{T(x_0,B_1,B_2)} \quad \text{[signaling units/unit time]} \tag{4}$$

where S_r is the location registration cost coefficient [signaling units/LR event].

Assuming that L_c, S_p and S_r are constants specified by the system, and assuming that $\mathcal{D}$, v and λ_p can be estimated from collected personal mobility and call statistics, the problem of finding the best LA for a user becomes a constrained optimization problem of choosing the LA boundary parameters B_1 and B_2 once the renewal point for registration x_0 is known:

$$\min_{\{B_1,B_2\}} C = \min_{\{B_1,B_2\}}\left\{S_p\lambda_p\left(\frac{B_2-B_1}{L_c}\right)+S_r\frac{1}{T(x_0,B_1,B_2)}\right\} \tag{5}$$

$$\text{subject to} \quad B_1 \leq x_0 \leq B_2. \tag{6}$$

3 Optimization Studies

3.1 Position Optimization of Location Area

Fixing $L_{LA} = B_2 - B_1$, taking derivative of C with respect to B_1 and setting $\frac{dC}{dB_1} = 0$ results

$$B_1^* = x_0 + \frac{\mathcal{D}}{2v}\ln\left\{\frac{\mathcal{D}}{2vL_{LA}}(1-e^{-\frac{2v}{\mathcal{D}}L_{LA}})\right\}. \tag{7}$$

For the extreme cases, we have $B_1^* \to (x_0 - L_{LA}/2)$ as $\frac{\mathcal{D}}{v} \to \infty$ and $B_1^* \to x_0$ as $\frac{\mathcal{D}}{v} \to 0$. Figure 3 shows B_1^* and $B_2 = B_1^* + L_{LA}$ as functions of v for two different values of $\mathcal{D}$ as L_{LA} is fixed.

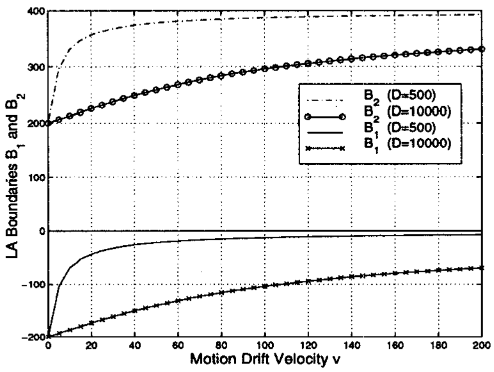


Figure 3: *Effect of the motion drift velocity v and diffusion constant $\mathcal{D}$ on LA positioning, assuming LA size $L_{LA} = B_2 - B_1 = 400$ and the user initial position $x_0 = 0$.*

For the optimal positioning of an LA, we observe the following results. When there is no motion drift ($v = 0$), the LA must be placed symmetrically with respect to the location registration renewal point x_0, i.e., x_0 is always at the center of the new LA after each registration. When drift velocity $v \neq 0$, it is particularly interesting to look at the result that LA positioning becomes skewed with respect to x_0. the LA must be shifted in the direction of v and the distance shifted increases with v as shown in Figure 3.

Diffusion constant $\mathcal{D}$ represents a motion uncertainty region around the initial position x_0. When $\mathcal{D}$ is small, the uncertainty region is small. While with larger $\mathcal{D}$, there is a larger region, indicating that more cells between x_0 and B_1 that needs to be included in the new LA. Motion with larger v and smaller $\mathcal{D}$ suggests more deterministic motion, while motion with smaller v and a larger $\mathcal{D}$ represents a more random motion that needs a larger LA to cover it.

3.2 Size Optimization of Location Area

Similarly, we optimize the overall cost function with respect to the LA length L_{LA}. When there is no motion drift ($v = 0$), we have the following analytical results:

$$B_1^* = x_0 - \frac{L_{LA}}{2} \tag{8}$$

$$L_{LA}^* = 2\left(\frac{S_r \mathcal{D}}{S_p \lambda_p} L_c\right)^{\frac{1}{3}} \tag{9}$$

which minimize the cost function and give the value of C as

$$C_{min} = 3\left(\frac{S_p \lambda_p}{L_c}\right)^{\frac{2}{3}} (S_r \mathcal{D})^{\frac{1}{3}}\ . \tag{10}$$

When motion drift $v \neq 0$, we can only solve the problem numerically. Figures 4, 5(a) and 5(b) show the overall cost as a function of the LA size for various values of parameters v, $\mathcal{D}$ and λ_p, respectively. The optimal LA size L_{LA}^* corresponds to the lowest point of the curves in these figures. We can define a useful ratio $\mathcal{D}/\lambda_p$ as the *mobility index* [1,2,4] which describes the average location uncertainty in (length^2/call), or simply how far on average a user moves between arriving calls of a user.

From the analytic and numerical results, we observe the following. As v increases, the optimum LA size L_{LA}^* increases accordingly as in Figure 4. The minimum cost C_{min} is also growing with v. This clearly indicates that a user with higher motion speed needs a larger LA and costs more for the system to track.

Moreover, L_{LA}^* grows as $\mathcal{D}$ increases and λ_p decreases, as in Figures 5(a) and 5(b). This indicates that if a user is location-volatile and receives calls less often, it is better to have a larger LA. While if a user moves less and receives more calls, a smaller LA is more appropriate. Figure 6(a) and 6(b) plot L_{LA}^* and C_{min} against the mobility index $\mathcal{D}/\lambda_p$ which shows that a high mobility index user requires a large LA and costs more as compared to a low mobility index user.

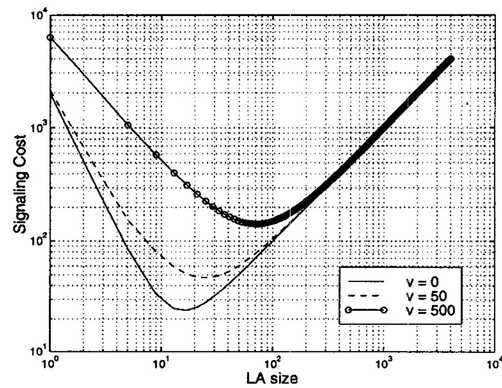
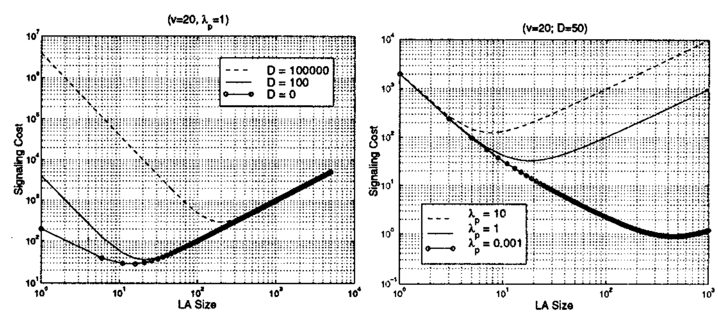
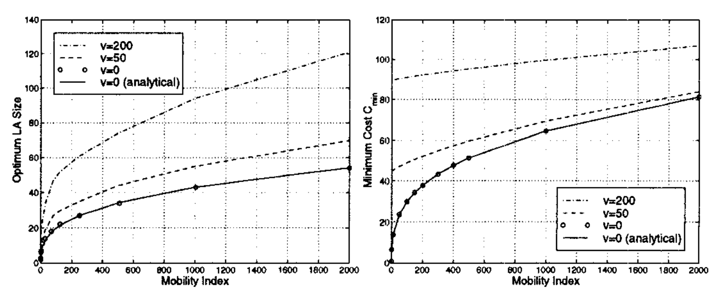


Figure 4: *Overall signaling cost with respect to LA size for various velocity v ($\mathcal{D} = 50$, $\lambda_p = 1$).*



(a) *Effect of $\mathcal{D}$ on the cost* (b) *Effect of λ_p on the cost*

Figure 5: *Overall signaling cost function for different location uncertainty $\mathcal{D}$ and mean call arrival rate λ_p.*



(a) L_{LA}^* *vs.* $\frac{\mathcal{D}}{\lambda_p}$ (b) C_{min} *vs.* $\frac{\mathcal{D}}{\lambda_p}$

Figure 6: *Optimum LA size L_{LA}^* and minimum cost C_{min} as a function of the mobility index $\frac{\mathcal{D}}{\lambda_p}$ for various velocity v (The numerical and analytical results converge at $v = 0$).*

4 Performance Analysis

Assuming the same mobility model (v, $\mathcal{D}$), call arrival model (λ_p) and system parameters (S_p, S_r, L_c) in the following, we compare the minimum cost C_{min} of the Adaptive LA Tracking Scheme proposed here with that of the Dynamic LA Management Scheme [1,2] proposed previously.

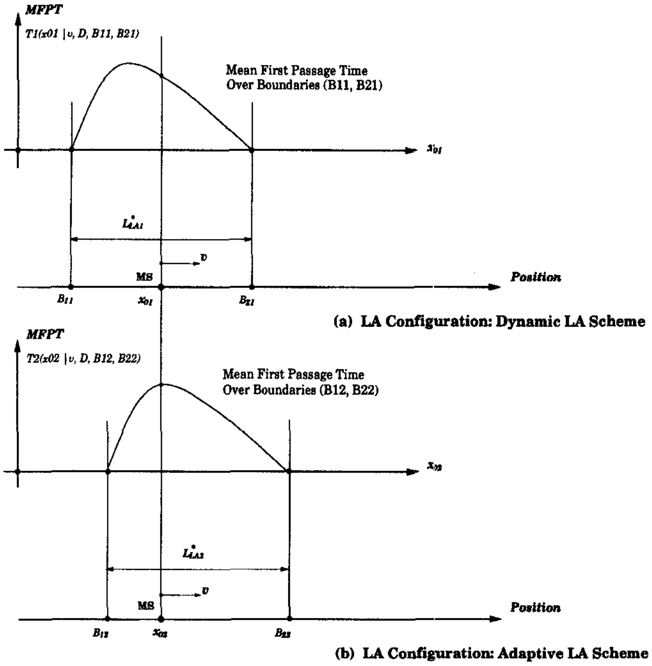


Figure 7: *The optimum LA configurations for (a) Dynamic LA Scheme and (b) Adaptive LA Scheme, and their corresponding MFPT as function of the MS starting point x_{01} or x_{02}.*

Figure 7 shows the configurations of the respective optimum LAs for the two schemes relative to the starting position of a user $x_0 = x_{01} = x_{02}$, together with the curves of the mean first passage time (MFPT) over the specified LAs (refer to equation (2)). The Dynamic LA Scheme has the boundaries of an LA always placed symmetrical to the starting position x_{01}. Whereas, Adaptive LA Scheme skews the LA relative to the starting position x_{02} when $v \neq 0$, and LA is shifted in the direction of v to make the x_{02} correspond to the *peak* of its MFPT curve. Clearly from the configurations, the Dynamic LA Scheme can not achieve the peak value of the average user dwell time in a LA since x_{01} is always fixed at the LA center.

The minimum costs C_{min}s of both schemes can only be obtained numerically using the following formulas:

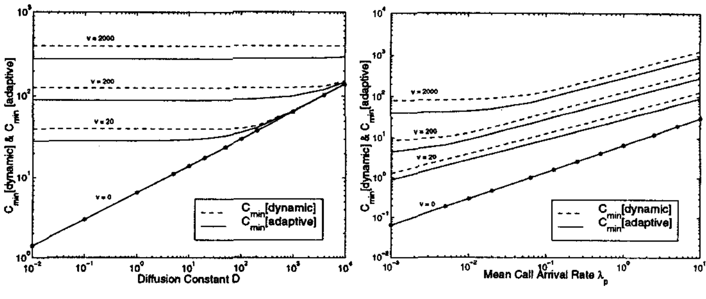
$$C_{min}[\text{dynamic}] = S_p\lambda_p N\left\{\frac{L^*_{LA1}}{L_c}\right\} + S_r\frac{1}{T_1(B_{11}, L^*_{LA1})} \quad (11)$$

$$C_{min}[\text{adaptive}] = S_p\lambda_p N\left\{\frac{L^*_{LA2}}{L_c}\right\} + S_r\frac{1}{T_2(B_{12}, L^*_{LA2})} \quad (12)$$

where T_1 and T_2 are MFPTs for the two schemes (refer to equation (2)). B_{11}, B_{12} are the lower boundaries of LAs (refer to equation (7)):

$$B_{11} = x_{01} - \frac{L^*_{LA1}}{2}, \quad (13)$$

$$B_{12} = x_{02} + \frac{\mathcal{D}}{2v}\ln\left[\frac{\mathcal{D}}{2vL^*_{LA2}}(1 - e^{-\frac{2v}{\mathcal{D}}L^*_{LA2}})\right]. \quad (14)$$



(a) *Compare C_{min} w.r.t $\mathcal{D}$* (b) *Compare C_{min} w.r.t λ_p*

Figure 8: *Minimum cost comparisons of two schemes versus location uncertainty $\mathcal{D}$ and mean call arrival rate λ_p.*

Comparing the numerical results plotted in Figures 8(a) and 8(b), obviously C_{min} of the Adaptive LA Scheme always lower-bounds that of Dynamic LA Scheme, except the case where the performance of these two schemes converges at zero speed $v = 0$ (starred lines). In Figure 9, we compute the cost ratio between those two schemes with respect to the average motion velocity, and we observe that the cost reduction increases with v and decreases with the mobility index $\mathcal{D}/\lambda_p$. The upper bound for cost reduction is 50%.

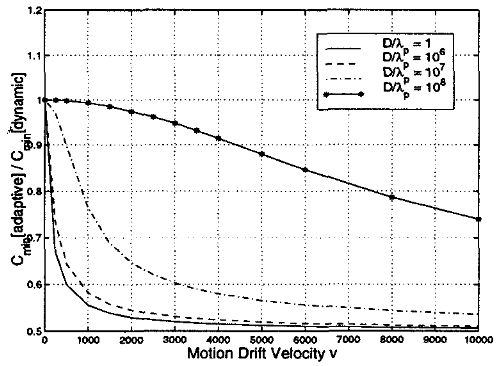


Figure 9: *Cost ratio (Adaptive/Dynamic) with respect to motion drift velocity for different values of mobility index $\mathcal{D}/\lambda_p$.*

A Numerical Example

Here we present a typical example which shows some specific results for a vehicular user in a one-dimensional highway cellular system using either the Dynamic LA Management Scheme [1,2] or the proposed Adaptive LA Tracking Scheme.

Let us consider a user that moves according to a one-dimensional random walk model [12]. The user moves in forward direction by one space step Δx with probability q and in reverse direction with probability $(1-q)$ for each time step Δt. As Δt and Δx steps tend to zero, this random walk model converges to a one-dimensional Brownian motion with drift model [12]. The actual traveling speed of the user $\mathcal{V} = \Delta x/\Delta t$.

Assuming $S_p = 1$, $S_r = 10$, $L_c = 1\ km$, and assuming $\lambda_p = 1\ calls/hr$ and $\mathcal{V} = 50\ km/hr$. Forward moving probability $q = 0.9$. The mobility parameters v and $\mathcal{D}$ can be calculated using formulas derived in [4,5], which give $v = 40\ \ km/hr$ and $\mathcal{D} = 0.5\ \ km^2/hr = 138\ \ m^2/s$.

The results computed are summarized in Table 1. This example shows a substantial cost reduction of more than 29% as compared to the Dynamic LA Scheme.

▲ Results	Dynamic LA	Adaptive LA
Optimum LA Size L^*_{LA}	28.4 $\rightsquigarrow$ 29 cells	20.2 $\rightsquigarrow$ 21 cells
LA Position $(x_0 - B^*_1)$	14.2000 $\rightsquigarrow$ 15 cells	0.0505 $\rightsquigarrow$ 1 cell
Minimum Cost C_{min}	56.5686 *units/hr*	40.0568 *units/hr*
Cost Comparison	1 *units/hr*	0.7081 *units/hr*
Relative Reduction		29.19%

Table 1: *Results of the Numerical Example: Dynamic LA Scheme vs. Adaptive LA Scheme.*

5 Discussion of System Issues

Generally, we assume that identical cells cover the linear service area contiguously and without overlapping. Each base station can be identified by a geographical coordinate y.

Each base station broadcasts its beacon signal containing the index y periodically to all the mobile users in its cell through the common broadcasting channel that users are monitoring. Each user keeps a list of the cell indices that comprise its current LA. Whenever a user enters a new cell by detecting a new y, it compares the cell index to its stored cell index list. If the new cell index does not belong to the stored list, then the user has left its current LA and must initiate a registration to report its new location.

When the network receives the registration request, it updates the location record of the user and computes the new LA for the user according to the estimated mobility and call parameters of the user in the previous LA. The new LA is represented by a new list of cell indices. The network sends this list back to the user to update its previous cell list. It is important to note that this scheme allows for lists to be compactly coded. For example, the actual cell list need not be passed back and forth, but rather, only a pair of boundaries indicating the first and last cells in the location area. From this a list may be computed.

6 Conclusions

This study provides insight into the mobility management problem on how to configure an individual location area (LA) for a user to achieve the minimum signaling cost, and shows the effect of the user's mobility and call characteristics on the cost performance of different strategies. Specifically, we have the following conclusions:

(1) The Brownian motion with drift mobility model chosen in the study is analytically tractable and reasonably versatile in that it characterizes two important aspects of individual user motion through motion drift velocity v and diffusion constant $\mathcal{D}$.

(2) The LA size depends on the average movement velocity, location uncertainty and mean call arrival rate of the user. Higher motion velocity or higher location uncertainty demand a larger LA and a higher tracking cost, while higher call arrival rate requires a smaller LA but also a higher cost.

(3) Besides LA size, LA shape (i.e., LA positioning in one dimensional case) plays an important role in signaling load reduction. Same-size LAs with different shapes can result in very different cost reductions with respect to a particular mobility pattern. This study suggests that while a user is moving in a given direction the probability mass of user location is *also* moving along in the same direction. Therefore the position of each new LA relative to the current location of the user should be shifted in the same direction to attain the maximum possible probability of user location and reduction in location registrations.

(4) Performance analysis shows that this scheme can offer a cost reduction up to 50% as compared to the Dynamic LA Management Scheme proposed previously [1, 2].

Our study of the proposed scheme here considers only a one-dimensional cellular system environment. For two-dimensional scenarios, it is extremely difficult to solve the problem following the same formulation here because the mean first passage time (MFPT) of a two-dimensional Brownian motion process in a bounded area of general shape is analytically hard to find. Some specific results of a two-dimensional MFPT in simple bounded areas are given in [8]. The two-dimensional mobility tracking problem can be solved by using a timer-based strategy [6, 7].

Future work should address the problem of how to design real-time estimators to measure the mobility and call traffic parameters such as v, $\mathcal{D}$ and λ_p of an individual user. The sensitivity of the minimum signaling cost to the mobility and call traffic parameters is also a topic of future investigation.

References

[1] D.J. Goodman, H. Xie, "Intelligent Mobility Management for Personal Communications",*IEE Colloquium on Mobility in Support of Personal Communications*, London, England, June 1993.

[2] H. Xie, S. Tabbane, D.J. Goodman, "Dynamic Location Area Management and Performance Analysis" *Proc. 1993 43rd IEEE VTC*, Secaucus, New Jersey, May 1993, pp.536-539.

[3] C. Rose, R. Yates, "Minimizing the Average Cost of Paging Under Delay Constraints", *ACM Journal of Wireless Networks*, vol.1, no.2, 1995, pp.211-219.

[4] C. Rose, "Minimizing the Average Cost of Paging and Registration: A Timer-Based Method", *ACM Journal of Wireless Networks*, vol.2, no.2, pp.109-116, 1996.

[5] C. Rose, R. Yates, "Location Uncertainty in Mobile Networks: a theoretical framework", *IEEE Communications Magazine*, vol.35, no.2, February 1997.

[6] Z. Lei, C. Rose, "Probability Criterion Based Location Tracking Approach for Mobility Management of Personal Communications Systems", *Proc. IEEE Globecom 97*, Phoenix, Arizona, November 1997, pp.977-981.

[7] Z. Lei, C. Rose, "Wireless Subscriber Location Tracking for Adaptive Mobility Management", *WINLAB Tech. Report TR-131*, Rutgers University, September 1996.

[8] J.M. Brázio, N.S. Silva "Performance Evaluation of A Multi-Layer Location Update Method", *Proc. VTC 96*, Atlanta, Georgia, April-May 1996, pp.96-100.

[9] R. Thomas, H. Gilbert and G. Mazziotto, "Influence of the Movement of the mobile station on the performance of a radio cellular networks",*Proc. 3rd Nordic Seminar on Digital Land Mobile Radio Communication*, Paper 9.4, Copenhagen, Sept. 1988.

[10] K.S. Meier-Hellstern, E. Alonso, D. O'Neil, "The Use of SS7 and GSM to Support High Density Personal Communications", *Conf. Record, ICC'92*, Chicago, IL, June 1992, pp.1698-1702.

[11] S. Karlin, Howard M. Taylor, *A First Course in Stochastic Processes*, 2nd ed., Academic Press 1975, Chapter 7, pp.340-391.

[12] W. Feller, *An Introduction to Probability Theory and Its Applications*, 2nd ed., John Wiley & Sons 1957.