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Predictive Distance-Based Mobility Management for PCS Networks

Zygmunt J. Haas and Ben Liang

Wireless Networks Laboratory

School of Electrical Engineering

Cornell University

haas@ee.cornell.edu

http://www.ee.cornell.edu/~haas/wnl.html

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Description of the Problem

- Personal Communications Services advocate ubiquitous network access to facilitate the exchange of information for nomadic end users independent of time, location, and access arrangements.
- The location of a mobile host must be identified before a connection can be established.

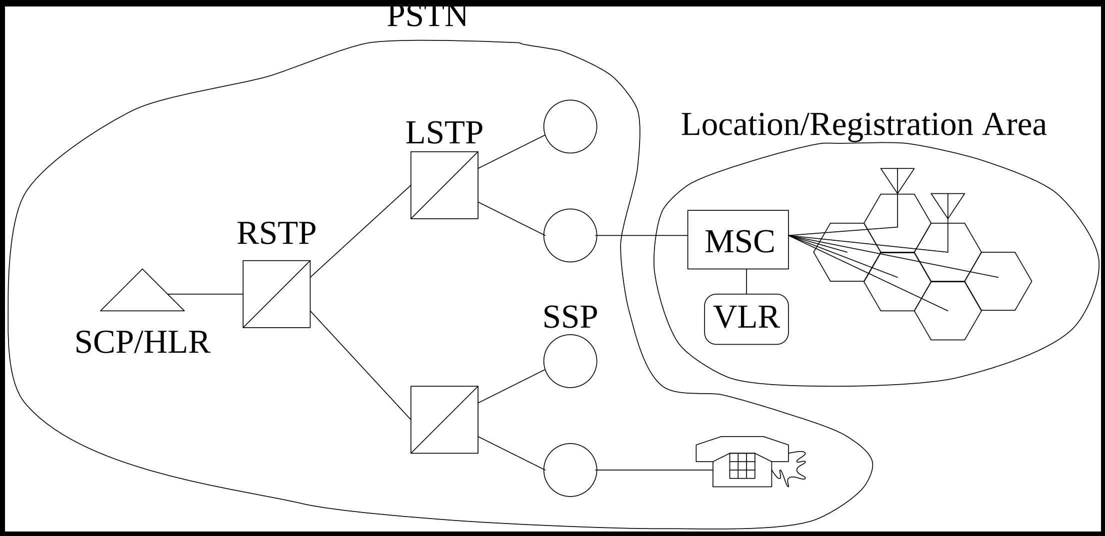
Description of the Problem (con't)

- **Mobility management functions include: user tracking and storage, maintenance, and retrieval of mobile host location information.**

- **Challenges: large service area; many users; limited bandwidth allocation; macro-cellular and micro-cellular environment; etc.**

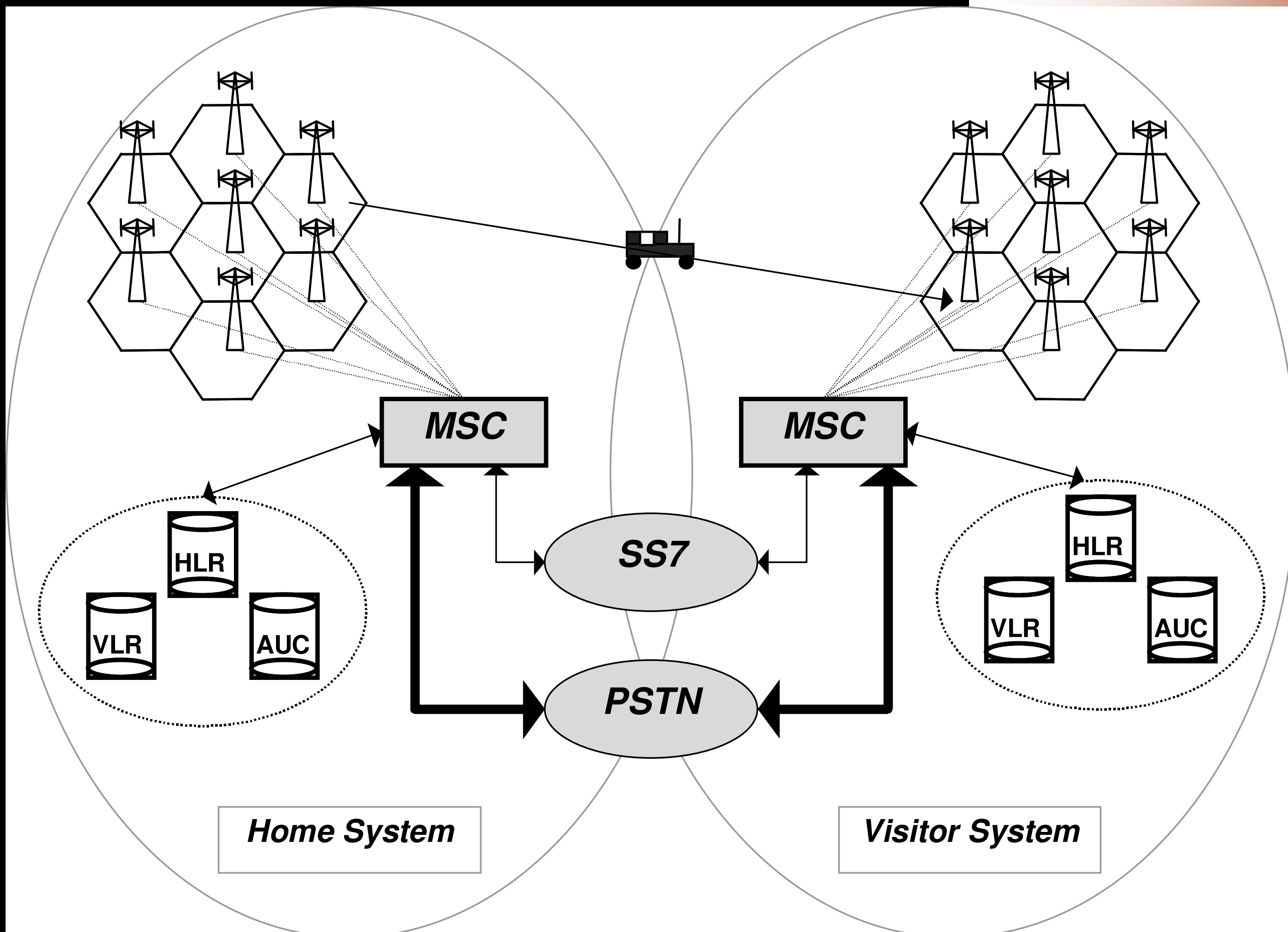
Previous Approaches

A. The HLR/VLR approach (e.g., IS-41 and GSM)



Static registration area cannot adapt to different and differing user traffic and mobility patterns.

Cellular Mobility



B. The dynamic registration area approach

[Xie, Tabbane, and Goodman, 1993]

- The registration area size is chosen on a per-user basis.
- The fluid-flow model of mobility is used.

C. The dynamic location update strategies

a. optimal location update decision via dynamic programming based on user traffic and mobility patterns [Madhow, Honig, and Steiglitz, 1995]

b. near optimal heuristic [Akyildiz and Ho, 1995]

c. mechanisms based on time, movement, or distance [Bar-Noy, Kessler, and Sidi, 1995]

In the above dynamic location update strategies:

- There is no fixed registration area.
- When a call arrives, the wireline backbone pages the cells around the last reported cell in a shortest-distance-first fashion.
- A mobile host decides whether to update or not based on the trade-off between the cost of updating and the cost of paging.
- The random-walk model of mobility is used.

The Shadow Cluster concept [Levine, Akyildiz, Naghshineh, 1995]

Our Mobility Model

- A mobile's velocity is correlated in time and modeled by a discrete Gauss-Markov process:

$$v_n = \alpha v_{n-1} + (1-\alpha)\mu + \sqrt{1-\alpha^2}\, x_{n-1}$$

$\alpha = e^{-\beta}$ and $\beta \geq 0$ is the memory factor

$\mu \geq 0$: the asymptotic mean of v_n as $n \to \infty$

x_n : independent uncorrelated Gaussian process with mean $= 0$, and standard deviation $= \sigma$

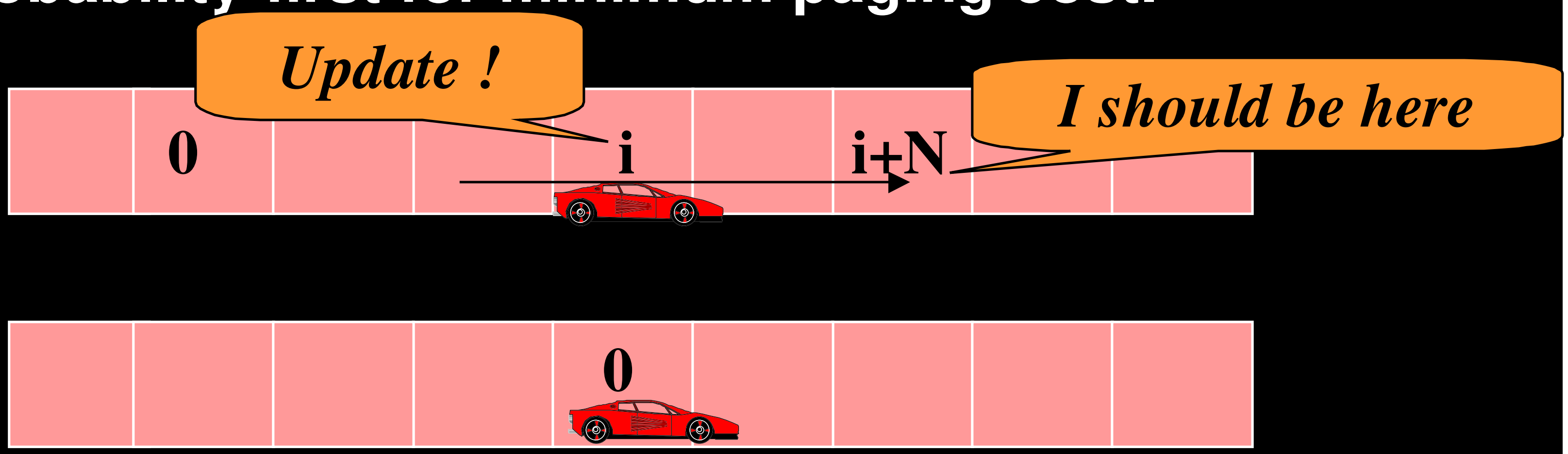
- This model more realistically represents user mobility in a PCS network.
- Includes the random-walk and the constant velocity fluid-flow models as two extreme cases.

Predictive Location Update and Tracking

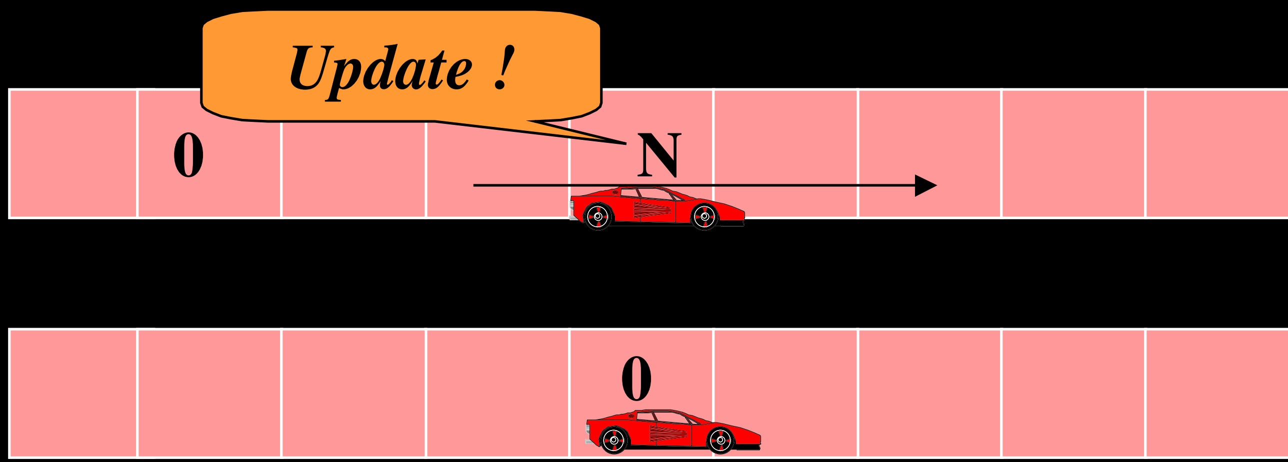
- A mobile's predicted future location is shared by both the wireline backbone and the mobile itself.
- Each mobile host performs a location inspection at every *m* clock ticks.
- At the time of location inspection, a mobile updates its location information to the wireline backbone if the mobile is more than *N* units of distance away from its predicted location.

Predictive Location Update and Tracking (con't)

- Upon a call arrival, the wireline backbone pages for a mobile in the cells around the predicted location of the mobile in a shortest-distance-first fashion.
- This scheme conforms to the rule of highest-probability-first for minimum paging cost.



Compared with Distance-based Updates



Analysis

- At the k^{th} location inspection since the last location update, a mobile's predicted location is

$$\mu_{s_k} = \mathrm{E}\left[\sum_{i=0}^{k-1}\sum_{j=im}^{im+m-1} v_j\right] = \frac{1-\alpha^{km}}{1-\alpha} v_0 + k\left(m - \frac{1-\alpha^m}{1-\alpha}\right)\mu$$

  where v_0 is the velocity of the mobile at time of the last location update.
- Let r_k be the distance to the predicted location at the k^{th} location inspection.

Analysis (con't)

Define $w_k = r_{k+1} - r_k$. We can compute the recursive relation

$$w_k = \alpha_k w_{k-1} + u_k \,, \quad \alpha_k = \frac{C_{k-1,k}}{C_{k-1,k-1}} \,, u_k = \sqrt{1 - \frac{C_{k-1,k}^2}{C_{k-1,k-1} C_{k,k}}} \, z_{k-1}$$

where $C_{i,j}$ is the auto-covariance of w_k ,

$$C_{k,k} = \sigma^2 \frac{-\alpha^{2km}(1-\alpha^m)^2 + m(1-\alpha^2) - 2\alpha(1-\alpha^m)}{(1-\alpha)^2}$$

$$C_{k-1,k} = \sigma^2 \frac{(1-\alpha^m)^2(\alpha - \alpha^{2km-m})}{(1-\alpha)^2}$$

and z_{k-1} is a Gaussian process, independent of w_k , with variance $C_{k,k}$.

- The following algorithm computes $f(k)$, the PDF of the time interval between two consecutive location updates.

  Define

  - $p_{r(k)w(k-1)}(r,w)$: probability that $r_k=r$ and $w_{k-1}=w$, and no update up to time $k-1$
  - $q_{r(k)w(i)}(r,w)$: probability that $r_k=r$ and $w_i=w$, and no update up to time k, $i=k-1,k$
  - $h_N(r) = 1$, if $-N < r < N$; $h_N(r) = 0$, otherwise
  - $\underline{F}(k)$: probability that there is no update up to time k

Initialization

- $f_{w0}(w) = \dfrac{1}{\sqrt{2\pi C_{0,0}}}\exp\left(-\dfrac{w^2}{2C_{0,0}}\right)$
- $p_{r1w0}(r,w) = f_{w0}(w)\delta(r-w)$
- ***k = 1***

Iterations

- **Step 1.** $q_{r(k)w(k-1)}(r,w) = p_{r(k)w(k-1)}(r,w)h_N(r)$
- **Step 2.** $\underline{F}(k) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} q_{r(k)w(k-1)}(r,w)dwdr$
- **Step 3.** $q_{r(k)w(k)}(r,w) = 1/\alpha_k \cdot q_{r(k)w(k-1)}(r,w/\alpha_k) * f_{uk}(w)$
- **Step 4.** $p_{r(k+1)w(k)}(r,w) = q_{r(k)w(k)}(r-w,w)$
- **Step 5.** ***k = k + 1*** **; repeat from Step 1, until *$\underline{F}$(k)* is sufficiently small**

f(k) = $\underline{F}$(k-1) - $\underline{F}$(k)

- At time *t* after the last location update, the PDF of a mobile's distance to the predicted location is

$$g(t,r)=\frac{\int_{-\infty}^{\infty} q_{r(t)w(t-1)}(r,w)dw}{\int_{-N}^{N}\int_{-\infty}^{\infty} q_{r(t)w(t-1)}(r,w)dwdr}$$

- When a call arrives, the PDF of time elapsed since the last location update is

$$p(t)=\lambda e^{-\lambda t}\int_{t}^{\infty}\frac{f(\tau)}{1-e^{-\lambda\tau}}d\tau$$

where λ is the call arrival rate.

- Given C_p, the cost of paging per cell. The average paging cost per unit time is

$$C_{page}=\lambda C_p\int_{0}^{\infty} p(t)\int_{-N}^{N} g(t,r)(2\,\mathrm{ceil}(r/S)+1)drdt$$

- The expected number of location updates within the interval of time t between two successive call arrivals is

$$M(t) = \sum_{i=1}^{\infty} \int_0^t f^{(i)}(\tau)d\tau$$

where $f^{(i)}(t)$ is given recursively by $f^{(1)}(t) = f(t)$, and $f^{(i)}(t) = f^{(i-1)}(t)*f(t)$.

- Given C_u , the cost per update. The average updating cost per unit time is

$$C_{update} = \lambda C_u \int_0^{\infty} \lambda e^{-\lambda t} M(t)dt$$

- The total cost per unit time is

$$C_{total} = C_{update} + C_{page}$$

Numerical Results

- For comparison, the cost of the regular non-predictive distance-base scheme is determined via simulations.

- In each scheme, the optimal threshold distance N is found, which incurs the minimum C_{total} . Performance gain of the predictive scheme is defined as min(C_{total}(non-predict)) / min(C_{total}(predict)).

Numerical Results (con't)

- Normalizing all costs to the unit of C_p , the performance gain is a function of six parameters, consisting of the mobility pattern (β , μ , σ), the call arrival rate λ , the relative updating cost C_u , and the location inspection period m .

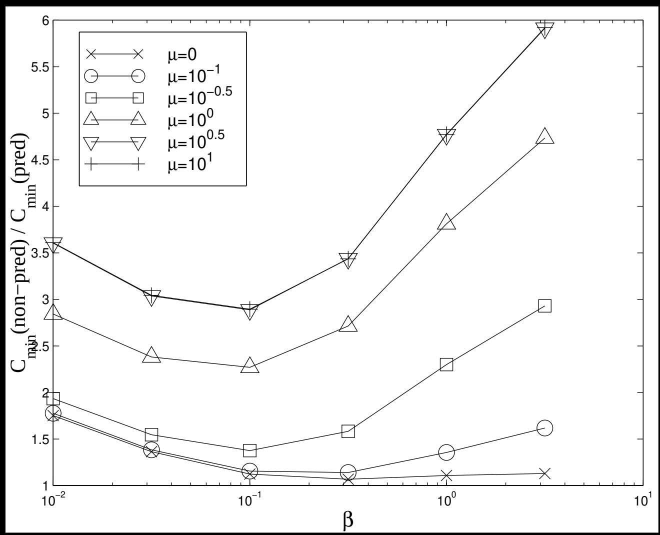


Fig. 1. Performance gain vs. β and μ for λ*=0.01*, C_u*=10*$^{0.5}$, *m=10*, and σ*=0.5*

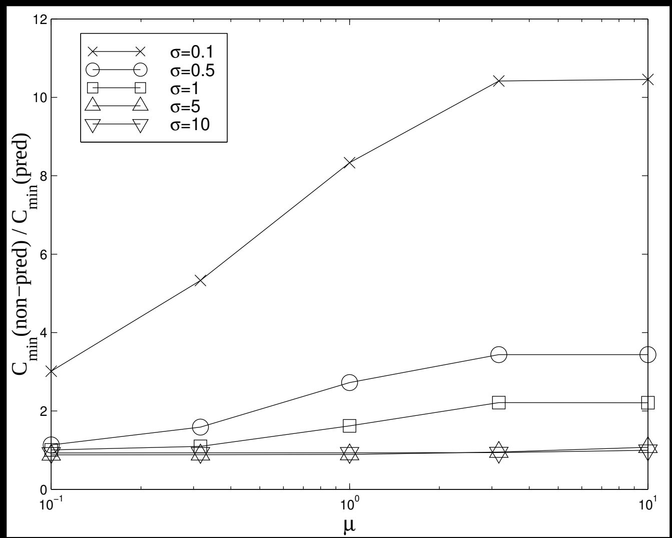
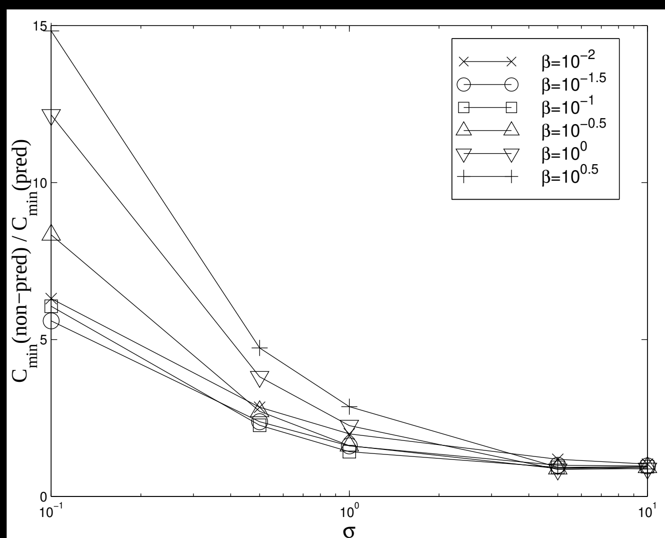


Fig. 2. Performance gain vs. μ and σ for λ*=0.01*, C_u*=10*$^{0.5}$, *m=10*, and β*=10*$^{-0.5}$ (α*=0.73*)



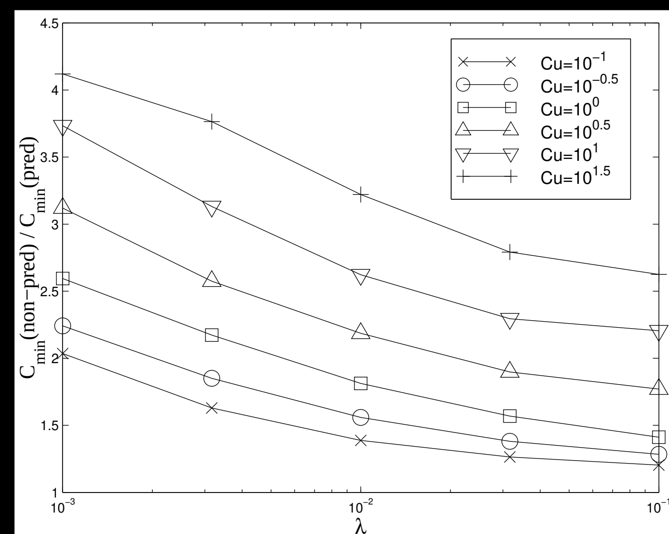


Fig. 3. Performance gain vs. σ and β for λ*=0.01*, C_u*=10$^{0.5}$*, *m=10*, and μ*=1*

Fig. 4. Performance gain vs. λ and C_u for μ*=0.5*, σ*=0.5*, β*=10$^{-0.5}$* and *m=5*

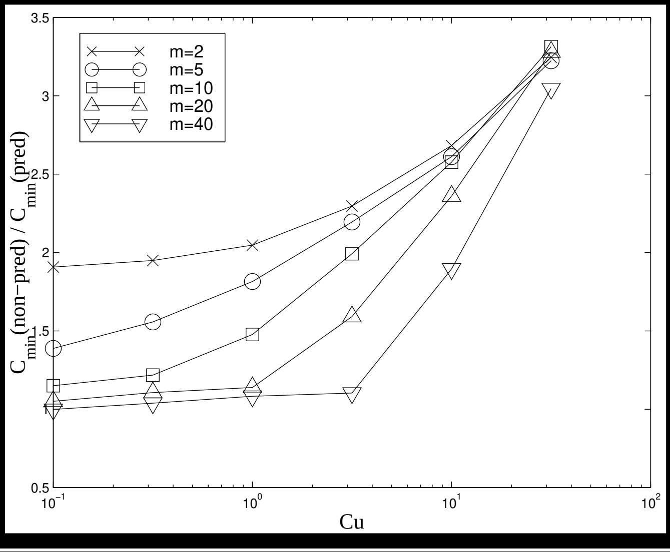


Fig. 5. Performance gain vs. C_u and *m* for $\mu=0.5$, $\sigma=0.5$, $\beta=10^{-0.5}$ and $\lambda=0.01$

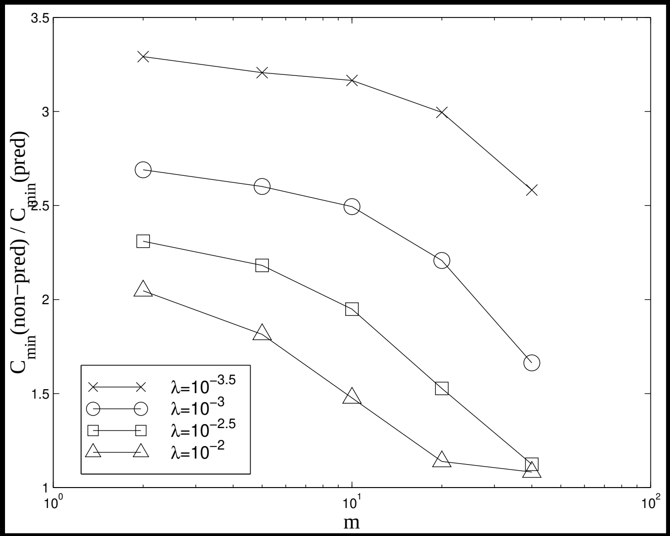


Fig. 6. Performance gain vs. *m* and λ for $\mu=0.5$, $\sigma=0.5$, $\beta=10^{-0.5}$ and $C_u=1$

Conclusions

- Mobile users in PCS networks have wide variety of mobility and traffic patterns.
- The registration-area-based mobility management schemes are not flexible.
- Most existing dynamic schemes assume either fluid-flow or random-walk mobility model.
- The Gauss-Markov model more realistically captures the various degrees of correlation of a mobile user’s velocity in time.

Conclusions (con't)

- The proposed predictive distance-based mobility management scheme takes full advantage of the time correlation in velocity and location, based on the Gauss-Markov model.
- The proposed analytical framework allows the evaluation of the predictive scheme given various user traffic and mobility patterns and system operating parameters.

Conclusions (con't)

- In the span of parameter values under consideration, numerical analysis shows that the predictive performance gain ranges from unity to a factor of more than 10.

- Future works: study the trade-off between the performance gain and the cost of prediction; develop multi-dimensional analytical frameworks for cost evaluation; investigate how imperfections in the Gauss-Markov representation affects the performance gain.