# Modeling Location Management in Personal Communications Services

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***Abstract*— This paper presents a realistic modeling framework for evaluating the performance of location management schemes in PCS networks. The framework captures complex human behaviors and has been validated through analysis of actual call and mobility data. Simulation results, showing the performance of IS-41, are presented.**

## I. Introduction

Personal Communications Services (PCS) [2] presents many challenging problems in network data management [6;18]. A key problem in this area is *location management*. Location management refers to accessing and maintaining user information for call routing purposes. Important per-user information, such as current location, authentication information, and billing information, are stored in *user profiles*. From an operational perspective, location management relies on two functions: *profile lookups* and *profile updates*. The performance of any location management scheme is a function of the underlying database architecture and the location management algorithms. Performance variables of interest are: profile lookup and update response times, memory cost, and system equipment price. Previous studies [10] have shown that for projected numbers of PCS users, existing location management standards, IS-41 [4;11] and GSM [12], will incur a large increase in database loads over the current levels. In recent years, many sophisticated location management schemes [7;14] have been proposed to reduce profile lookup and update response times and signaling traffic. These methods utilize techniques such as data replication and caching. It is important to note that actual performance of these proposals depends strongly upon user behavior. For example, the merits of caching and data replication schemes are functions of user mobility and calling patterns. As a result, realistic user behavior models are a critical aspect in performance evaluation.

In this paper, we present a framework for modeling and evaluating location management schemes in a PCS environment. The main contributions are that we have developed and validated models, through analysis of real call and mobility data, that can capture complex human behaviors. Our callee distribution and movement models are more realistic than the models commonly used in this area of research. We illustrate the importance of our detailed user behavior models by showing how other simpler models produce significantly different results in key performance variables. In addition, our framework models time-varying behaviors which allow us to investigate transient, peak, and average performance. Our framework therefore, unlike other synthetic ones, provides a platform for generating more realistic simulation results. We have developed a discrete event simulator, *Pleiades*, based on our framework. Using Pleiades, we have compared our models with other simpler ones and studied the performance of IS-41, over a 24-hour period, for a large number of PCS subscribers on a model of the San Francisco Bay Area. Comparisons and simulation results are presented in terms of database transaction requirements and signaling traffic loads.

The rest of the paper is organized as follows. Section 2 describes our modeling framework. Section 3 presents our model comparisons and Bay Area simulation results. Section 4 concludes the paper.

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## II. Modeling Framework

We have developed a modeling framework for realistic performance evaluations of sophisticated location management schemes. Our framework is divided into the following components: **Basic Topology Model**, **Call Model**, and **Movement Model**. The Basic Topology Model specifies the geographical and network topologies independent of location management schemes. Call and Movement Models characterize call and movement behavior of individual users.

### A. Basic Topology Model

The Basic Topology Model is composed of the following objects.

**User** represents a human user. A user object contains information describing the user's current geographical location, the user's home location, and the database(s) currently containing a copy of the user profile.

**Site** represents a geographical area. All Site objects together define the physical geography for user movements. A Site usually corresponds to the area covered by one profile database.

**Database** represents any form of user profile database. A Database is often associated with a Site. Each database object maintains access statistics relating to number of database reads and writes, database messages sent, and total cost of sending all database messages (e.g. in hop counts).

**Link** represents a direct communication link between two databases. It has a link cost describing the cost of sending a message through it. It maintains traffic statistics in terms of number of messages.

Geographical topology is defined by a *movement connectivity matrix* which specifies, for each Site, its neighbors and the probabilities of users crossing into each of them. Network topology for communications between databases is specified through the Link objects.

*B. Call Model*

Our call model generates call traffic for each individual user. The model is divided into two parts: the **Call Traffic Model** and the **Callee Distribution Model**. We have corroborated our models using encrypted call traffic data [15] from our local university telephone exchange. This exchange serves the entire campus including university offices, student housing, and faculty and staff residential households.

### A. Call Traffic Model

The call traffic model describes how often individual users place calls to other people and characterizes the duration of each call. Very little is known about the traffic characteristics of future PCS networks. However, on fixed telephone networks, traffic is modeled accurately. Mean call arrival rate and mean call duration during busy hours have been reported in [10]. Our call traffic model is an extension of the fixed telephone traffic model to PCS. It generates call arrivals (i.e., calls initiated) for different classes of traffic and models time-varying user behavior. Each call traffic class is characterized by its probability of occurrence, call arrival rate, mean call duration, and distribution.

We have investigated time-of-day call traffic volume patterns because we need to use corresponding mobility patterns in performance evaluation. Figure 1 shows the traffic volume patterns derived from [15]. These patterns and call arrival rates in [10] provide guidelines for us when specifying the parameters in our Call Traffic Model.

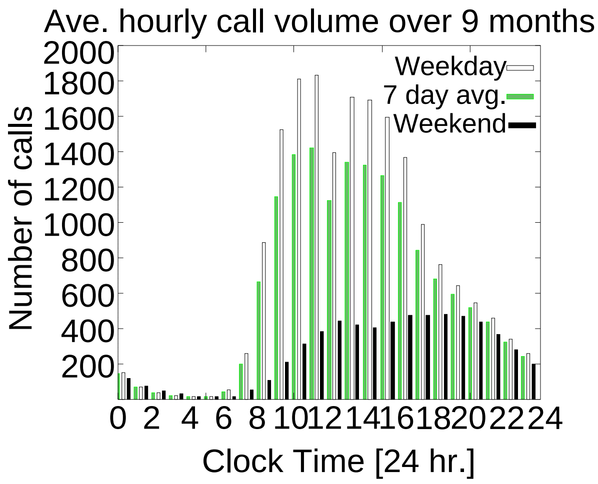


Fig. 1. Average Number of Call Arrivals Per Hour

| Time Scale | $A$ | $p$ | mean sq. error |
|---|---|---|---|
| 1 Day | 0.778 | 2.61 | 0.000010 |
| 1 Week | 0.574 | 1.84 | 0.000028 |
| 1 Month | 0.383 | 1.34 | 0.000030 |

Table 1. Fitted Power Law Parameters

### B. Callee Distribution Model

The callee distribution model characterizes how the callee is generated for each call. It is an important modeling issue because of its effects on performance evaluation, especially for schemes with caching or data replication. To the authors' knowledge, there has not been any previous research in this area.

We have developed a callee distribution model that models the behavior of each individual caller. It accounts for such real life behaviors as users calling a group of people (e.g., business associates and friends etc.) more frequently. In our model, each user is associated with its own callee list. When a call is generated for a user, the callee is selected either randomly from all users or from among the user's callee list according to a specified probability distribution. To obtain reasonable parameters, we have investigated empirical probability distributions using the notion of *callee rank*. The rank $k$ callee of a caller is the caller's $k^{th}$ most frequently called person within a reference period. For each caller $i$ in [15], we calculate the call probability to the rank $r$ callee ($\hat{P}^i_r$) over the periods of 1 day, 1 week, and 1 month. We observe that the mean call probability to the rank $r$ callee, $\bar{P}_r$, can be modeled using a power or generalized Zipf's law at all three reference time periods: $\bar{P}_r \simeq \frac{A}{r^p}$, where $A$ is the scaling parameter and $p$ is the exponent parameter. Table 1 shows the fitted parameters and mean square errors of the fits. Figure 2 and Figure 3 are linear and log-log plots of $\bar{P}_r$ versus callee rank for the three reference periods.

We have investigated distributions around $\bar{P}_r$ because we want to include in our model callers that deviate from the "average" behavior. Figure 4 shows the distributions of $\hat{P}^i_1$ for the three reference periods. We modeled each empirical distribution with a truncated normal distribution. Figure 5 shows the cumulative distributions of $\hat{P}^i_1$ and their fits to our model. For the higher rank call probabilities, we looked at the relative probabilities to the rank $r$ callee, $\hat{P}^i_r/\hat{P}^i_{r-1}, r > 1$. We also modeled the distributions of $\hat{P}^i_r/\hat{P}^i_{r-1}$ by truncated normal distributions. Figure 6 shows graphically the cumulative distributions of relative call probabilities for a few higher rank cases and their fits to our model. We have implicitly assumed in our call model that callee distributions are not dependent on call arrival characteristics. We have verified this assumption by observing that low correlation exists between callers' average call arrival rates and their observed call probabilities. Table 2 summarizes this result in terms of correlation coefficients between average call arrival rates of users over the reference time periods and their respective call probabilities.

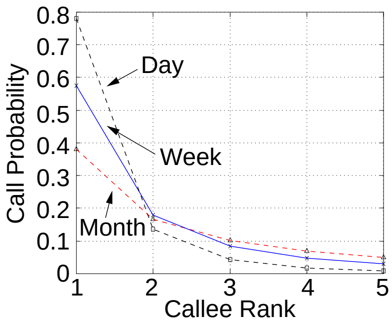


Fig. 2. Mean Call Probability vs. Callee Rank

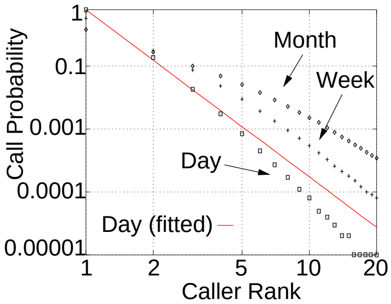


Fig. 3. Log-Log Plot of Mean Call Probability vs. Callee Rank

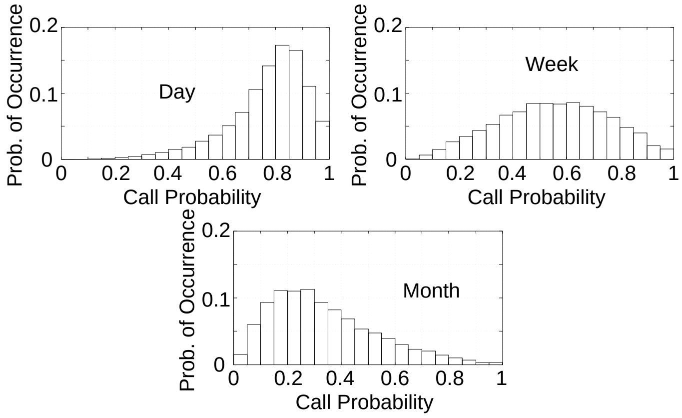


Fig. 4. Distributions of Call Probabilities to First Rank Callee (for three reference time periods)

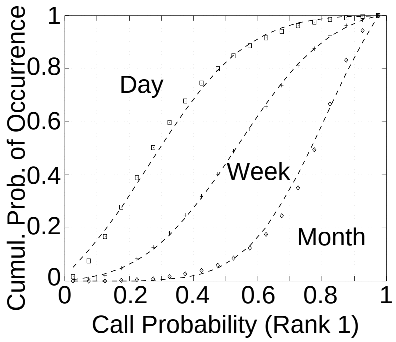


Fig. 5. Cumul. Distribution of Call Probabilities to First Rank Callee

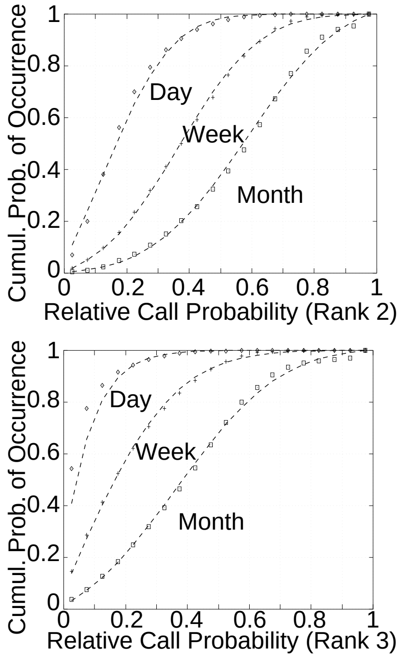


Fig. 6. Cumul. Distribution of Relative Call Probabilities to Higher Rank Callees

| Time period | $\hat{P}_1$ | $\hat{P}_2/\hat{P}_1$ | $\hat{P}_3/\hat{P}_2$ |
|---|---|---|---|
| 1 Month | -0.0009 | 0.0014 | 0.0018 |
| 1 Week | 0.0016 | 0.0004 | 0.0003 |
| 1 Day | 0.0033 | -0.0011 | -0.0027 |

Table 2. Correlation between Average Call Arrival Rates and Call Probabilities

### *C. Movement Model*

Our movement model characterizes user movements within the geography defined by the Basic Topology Model. Instead of a simple Markovian model as in [1], we have developed a more detailed model, which includes the Markovian model as a special case, because most proposed location management schemes optimize their performance for certain movement characteristics. For example, *return home* movements are important when studying schemes with home location registers (such as IS-41 and GSM). Our model generates movements corresponding to different classes of mobility behavior: *simple move*, *roundtrip move*, *return home move*, and *stationary move*. Each of the movement classes is characterized by its probability of occurrence, mean velocity and distribution, mean number of site crossings and distribution.

We have investigated actual user movement behavior using survey results from [3;5;8] and actual movement statistics from [13]. Figure 7 is a summary of the time-of-day traffic volume patterns we obtained from [5;13]. From the data in [5], we have derived statistics (see Table 3) relating to mode of transportation, travel distance, and travel time statistics for various movement types and their percentages of occurrence. In our movement model, we then represent

| Trip Purpose | % of Trips | Ave. Trip Len. (mi) | Ave. Vel. (mi/hr) |
|---|---|---|---|
| To/From Work | 20.2 | 10.65 | 31.3 |
| Work-Related | 1.4 | 28.20 | 81.3 |
| Personal | 52.9 | 6.74 | 28.3 |
| Social/Other | 25.3 | 11.53 | 39.2 |
| Vacation | 0.2 | 218.22 | 261.5 |

Table 3. Movement Statistics

each trip purpose in Table 3 as a movement class with their appropriate mean move velocity and distance.

## III. Simulation Results

We have developed a discrete event simulator, Pleiades, based upon the framework described above. Pleiades contains modules which perform the functions of various location management schemes, such as IS-41, GSM, and other novel proposals. The architecture of Pleiades is shown in Figure 8; further details on Pleiades can be found in [9].

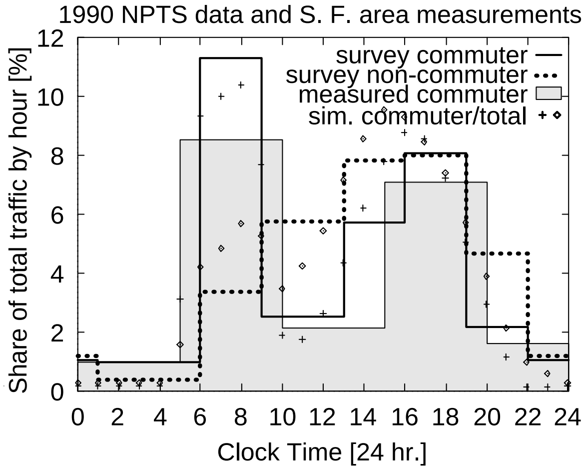


Fig. 7. Estimated Commuter Pattern from Traffic Measurements

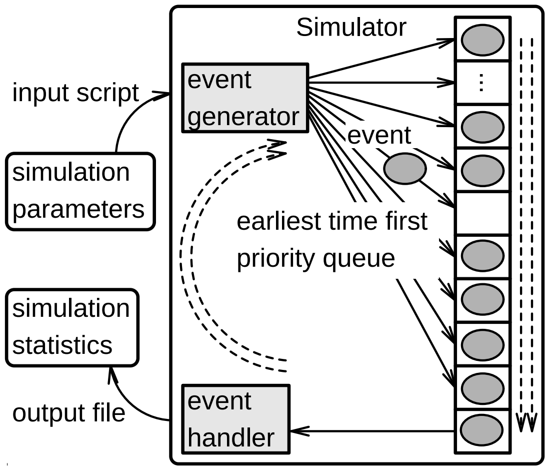


Fig. 8. Simulator Architecture

We now show that our callee distribution and movement models are critical to performance evaluation. Table 4 shows the simulation parameters. Tables 5 and 6 are summaries of simulation results for two location management schemes, IS-41 and centralized database. In the centralized database scheme, all user profiles are stored in one single centralized database. If the caller and the callee are not in the same registration zone, then a profile lookup is required at the centralized database. We observe that using our proposed models, significantly different results were obtained in the key performance measures. We note that, in the centralized database scheme, global average update rates are independent of the models because we need to update the same number of profiles per user movement.

Using Pleiades, we have investigated the performance of IS-41 on a geography that models the San Francisco Bay Area, which is composed of four area codes. Figure 9 is a map of the Bay Area. Regions corresponding to different area codes are represented by different shades in the figure; bridges, ferries and public transportation are also included.

| Parameters | Parameter Set 1 | 2 | 3 |
|---|---|---|---|
| # users | 16200 | | |
| Geography | 9x9 square grid | | |
| Callee Model | Proposed 8 callees | Random | Proposed 8 callees |
| Move Model | 25% no move<br>25% simple<br>25% roundtrip<br>25% return home | 25% no move<br>25% simple<br>25% roundtrip<br>25% return home | Markov |

Table 4. Simulation Parameters for Model Comparisons

| Perf. vars. (Global) | Set 1 | Percentage Difference (Set2-Set1)/Set1 | (Set3-Set1)/Set 1 |
|---|---|---|---|
| ave. lookup rates (per sec) | 26.02 | 21.1% | 18.2% |
| ave. update rates (per sec) | 42.74 | $\approx 0\%$ | 19.8% |
| ave. message rates (per sec) | 52.00 | 21.1% | 34.5% |
| ave. msg-hop count per sec | 112.9 | 49.8% | 31.8% |

Table 5. Simulation Results and Percentage Difference for IS-41

| Perf. vars. (Global) | Set 1 | Percentage Difference (Set2-Set1)/Set1 | (Set3-Set1)/Set 1 |
|---|---|---|---|
| ave. lookup rates (per sec) | 20.65 | 17.0% | 12.3% |
| ave. update rates (per sec) | 18.47 | $\approx 0\%$ | $\approx 0\%$ |
| ave. message rates (per sec) | 31.51 | 9.93% | 46.7% |
| ave. msg-hop count per sec | 68.54 | 40.4% | 46.3% |

Table 6. Simulation Results and Percentage Difference for Centralized Database Scheme

| Area Code region | Counties | 1990 Population | Sim. subreg. | Bord. subreg. |
|---|---|---|---|---|
| North Bay (707) | Solano, Napa, Sonoma | 839,408 | 8 | 4 |
| Peninsula (415) | S. F., San Mateo | 1,603,978 | 14 | 7 |
| East Bay (510) | Alameda, Contra Costa | 2,082,914 | 17 | 7 |
| South Bay (408) | Santa Clara, San Jose | 1,497,577 | 11 | 2 |
| Totals | 9 counties | 6,023,877 | 50 | NA |

Table 7. Population Figures

| | Simulated Times | | |
|---|---|---|---|
| Perf.vars (Global) | 12:45 p.m. | 13:00 p.m. | 15:25 p.m. |
| lookup rate (per sec) | 4,745.9 | 4,745.8 | 4,002.6 |
| update rate (per sec) | 529.5 | 558.3 | 741.2 |
| total rate (per sec) | 5,375.4 | 5,304.1 | 4,743.8 |

Table 8. Access Rate at Three Selected Simulation Times

Figure 10 [17] is an overlay map that shows the relationship between our simulation model and the actual geography of the Bay Area.

Using actual traffic volume statistics from [13], we have estimated movements between area codes [9]. Using an ad hoc approach, we specified the movement connectivity matrix to produce corresponding movement behavior between the area code regions in our simulation.

We simulated a 24-hour period for 3,025,000 users corresponding to approximately 50% of the current Bay Area population. We distributed the user population in our Basic Topology Model according to the census information obtained from [16] (see Table 7). Figure 11 and Figure 12 show systemwide database and network activities throughout the simulation. We note that in the following summary, peak lookup and update rates occur at different times. This is revealed only through our detailed time-varying models and suggests possible optimizations in the utilizations of network resources. The following summarizes the results.

- We observe peak access rate for lookups at 4,746 TPS, for updates at 741 TPS, and their combined total at 5,304 TPS. These peak rates occurred at 12:45 p.m., 3:15 p.m., and 1 p.m. in our simulated day, respectively. Table 8 shows lookup, update, and total access rates at these peak times.
- We observe a peak signaling bandwidth of 4,401 messages per second and 12,721 message-hops per second at 1 p.m. in our simulated day.

## IV. Conclusions

We have presented a framework for modeling and evaluating the performance of location management schemes in PCS. Our framework incorporates realistic behavior mod-

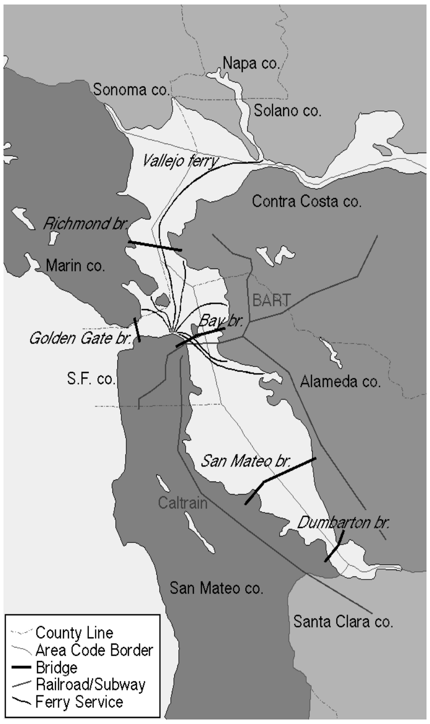


Fig. 9. Map of the San Francisco Bay Area

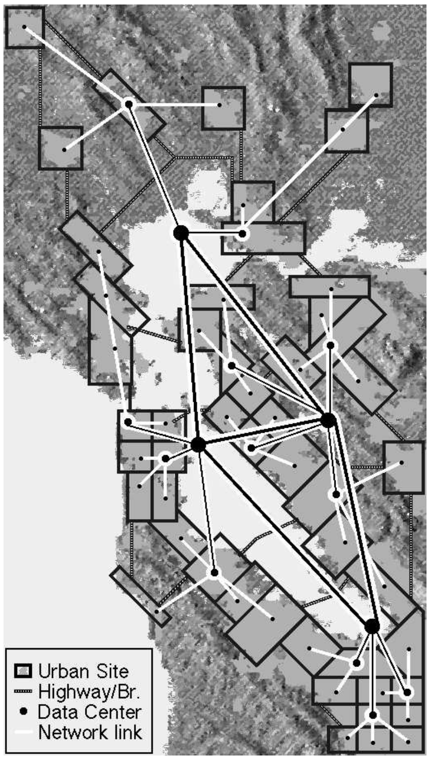


Fig. 10. Overlay of Simulation and Network Topologies

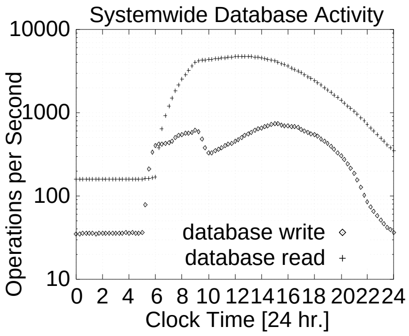


Fig. 11. Database Access Rate

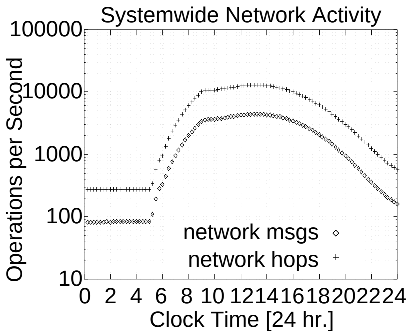


Fig. 12. Number of Database Messages

els that we corroborated using measurements and surveys of actual human activities. We have compared simulation results with some commonly used models and showed that our framework produced significantly different results in performance measures of key interest. We have developed a software system capable of simulating a large population of users and have presented results of a detailed 24-hour simulation of the San Francisco Bay Area. At a time when large scale wireless communication networks have not yet been implemented, our work provides a practical way to evaluate the performance of various location management proposals and to assess database transaction and network bandwidth requirements for providing PCS. Our simulation results suggest that, for a projected population of PCS subscribers, database and signaling requirements can be high and research on more efficient location management schemes is necessary.

## V. Acknowledgments

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