Characterizing and Modeling User Mobility in a Cellular Data Network

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ABSTRACT
The demand for cellular data networks is expected to increase with 3G and beyond technologies accompanied by high-bandwidth consumer services, such as wireless video and camera phones. User mobility affects quality of service, and makes capacity planning more difficult. This paper presents an analysis of user mobility patterns based on data traffic traces from a major regional *CDMA2000* cellular network. We find low overall mobility in the network, power-law characteristics in user mobility profiles, and weak correlations between call activity and mobility levels for individual users. We also find that users concentrate their activity in a "home cell" with frequent shorter trips to other locations in the network. Based on the empirical findings, we develop and parameterize a model of cellular data user mobility and show its practical use in simulation.

Categories and Subject Descriptors
C.4 [**Performance of Systems**]: *Measurement techniques, modeling techniques.*

General Terms
Measurement

Keywords
Network traffic measurement, Wireless, Cellular data networks, CDMA2000, User mobility

1. INTRODUCTION
With wide deployment of 3rd generation cellular technology (3G), such as CDMA2000 [1], network providers can offer many Internet data services to their subscribers. Such services include Web browsing, electronic mail, simple text and multimedia messaging, camera phones and gaming. Even more complex and sophisticated services are also emerging, e.g. low-bandwidth wireless video streaming, home security monitoring, and peer-to-peer file sharing.

Provisioning the network for the increased bandwidth demand is complex, as the new data services can have a dramatic impact on the usage of the cellular network, particularly as emerging applications grow in popularity and the user base expands. User mobility adds to the problem as it can affect capacity and quality of service planning, especially in CDMA networks, where soft handoff increases the complexity of network traffic management [4].

In addition to understanding data traffic characteristics [7, 9], an understanding of user mobility is required for proper provisioning of 3G and future cellular networks. The goal of this paper is to characterize the cellular user mobility and formulate a mobility model based on actual data traffic traces from a large CDMA2000 1x network.

We present a detailed analysis of user mobility behaviour from the packet data traffic traces collected from an operational cellular data network. We are not aware of any other study that characterizes cellular data user mobility based on low-level packet traces. The analysis in this paper focuses on one week-long trace data set, representative of the total of four weeks of collected data.

The most interesting results from our traffic analysis are heavy-tail characteristics in user mobility profiles, namely the frequency of location changes, roaming range, and number of calls per cell site. We find that many data users show little or no mobility. The roaming range is low, meaning that users generally visit a small portion of the network. It is further shown that both mobility level and roaming range are weakly correlated to the level of call activity.

From the empirical findings, we develop a user mobility model, including statistical distributions for the main parameters. Most parameters do not strictly follow standard statistical distributions and we employ different methods to make the best approximations. We further introduce a notion of "home cell" that applies to both stationary and mobile users, and has an important role in our user mobility model. Simulation results for each element of the model closely match the observed trace data.

We expect that the trace-based analysis and results presented in this paper will benefit research in user mobility, by providing empirical data for simulation models. Although the measurements are specific to this particular CDMA2000 1x cellular network, the results show that there are similarities to user behaviours in other wireless, and even wired networks.

The rest of this paper is organized as follows. Section 2 presents the related work. The methodology for this study follows in Section 3 and the analysis of results in Section 4. The mobility model and simulation results are discussed in Section 5. Section 6 concludes the paper.

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2. RELATED WORK

Most measurement studies of wireless networks are focused on traffic analysis rather than user mobility. WAP traffic is examined in several studies, as a popular protocol for wireless data communication. For example, WAP traffic is characterized and compared to Web browsing traffic in [10]. Both types of traffic exhibit self-similarity and daily/weekly usage periodicity, but WAP traffic sessions are shorter and data packets smaller than in Web traffic. Further studies show more differences between WAP and Web traffic, such as distinct look-up and browsing user scenarios, as well as different distributions for page inter-arrival times [11].

Important findings in broadband Internet traffic include a heavy-tail property [2, 3, 6, 12], and we show that the same behaviour also applies to wireless cellular traffic. Our results illustrate heavy-tail properties in user mobility level, roaming range, and number of calls per cell site.

In the domain of cellular networks, Shankaranarayanan et al. [14] present measurements of cellular voice and data users in a TDMA network, and use this information to parameterize user workload simulation models for a capacity planning study. A similar study by Varga et al. [17] presents a comprehensive model of WAP traffic over GPRS, with statistical distributions for parameters based on a long-term IP traffic trace from a major network. Adya et al. explore user browsing behaviour and identify heavy-tail relationships in object popularities [2, 3].

Further cellular traffic characterization was done by Klemm et al [8]. Their synthetic model is based on an IP traffic trace, and involves bandwidth scaling of traffic classes to the levels found in UMTS (3G) networks [16]. We present a model based on the actual low-level packet trace that is not specific to traffic classes (Web, email, etc.).

A study of a metropolitan radio wireless network by Tang and Baker [15] focuses on user mobility. This study employs an elaborate classification and clustering scheme to categorize users into activity, mobility, and daily usage groups. They find that most users have very little mobility, and that the number of location changes is inversely related to the roaming distance. We also find low overall mobility and categorize users by their overall activity and mobility levels.

Scourias and Kunz propose a mobility model for cellular users based on a subscriber survey involving logs of daily usage [13]. The users are grouped into socioeconomic categories and corresponding activities used to derive their daily mobility patterns as parameters for simulation of location management algorithms.

This paper complements earlier knowledge by studying user mobility in a large regional 3G cellular data network, using a low-level data traffic trace (excluding voice traffic). We explore mobility events, roaming range, load across the cell sites, as well as other parameters and their correlations.

3. METHODOLOGY

The data traces analyzed in this paper were collected from an operational CDMA2000 1x cellular data network in March 2004, with the cooperation of a cellular network provider and assistance from the vendors of the equipment used in the network. The measurements were collected by instrumenting vendor equipment

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MSID    5552490623
ESN     0xe3ce7469ace
SITE    7846
FREQ    384
START   2004 03 09 79525.080
ACTIVE  2004 03 09 79525.760
CID     287
SID     3
ACTIVE  2004 03 09 79526.240
CID     287
SID     3
CID     602
SID     2
   .
   .
   .
END     2004 03 09 79587.060
```

Figure 1: Trace data format shows the details of packet calls recorded.

to report all packet-level cellular network events involving mobile stations, the base station, and the base station controller. Event timestamps are recorded with 20 ms granularity.

The traces include low-level information about the events occurring between the mobile stations (i.e., cell phones), the base station (i.e., cell site), and the base station controller. The events indicate mobile station identifiers, as well as the start time, end time, cell site, sector id, and carrier frequency used for each packet data call. Within each packet data call, the trace also records information about fundamental channel and supplementary channel usage, including the data rate and duration for each supplementary channel data burst in the forward and reverse directions. Only packet data calls are recorded, not voice calls.

A total of 43 traces were collected from the cellular network. The traces were collected from several different measurement points, over the time span of 4 weeks. The individual traces range in duration from about 1 to 24 hours, depending on the location and the time of day. The aggregate set of traces represents over 480,000 packet data calls from over 10,000 cellular network users. The aggregate data set provides a large sample for the statistical analysis of network traffic characteristics and user mobility behaviour.

In this paper, we restrict our attention to one continuous week-long portion of the trace data from one measurement location, as a representative example of the cellular data network activity.

We use a custom-written analysis program to process the traces and summarize the statistical properties of the traffic observed. An example of the trace format is shown in Figure 1. This example shows one packet data call. The call originated from mobile station identifier (555) 249-0623 in region 7846 of the provider's network, using a frequency of 384 MHz. The call was placed on Tuesday March 9, 2004 at 10:05pm (79,525 seconds after midnight). The call lasted 62 seconds. The intermediate reports

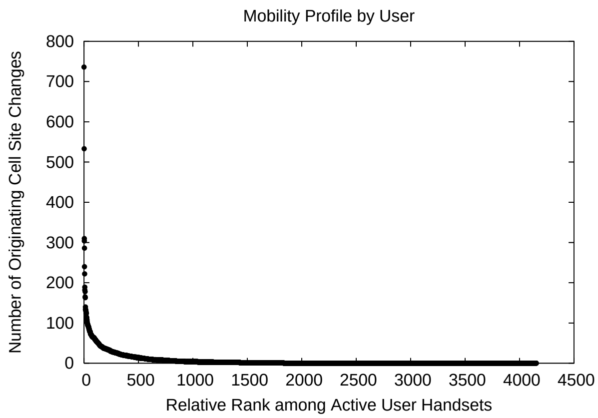

Figure 2: The distribution of number of cell changes among users is highly skewed.

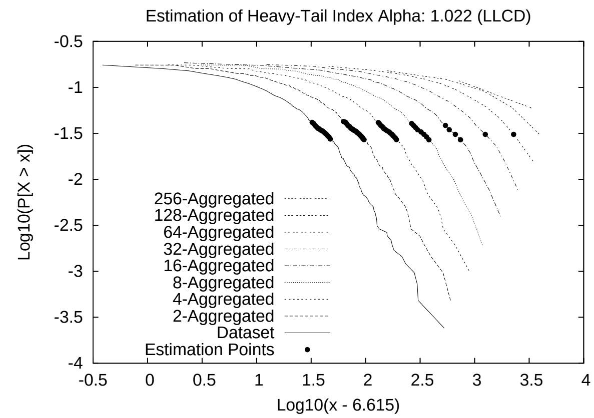

Figure 3: Heavy-tail behaviour appears in user mobility level.

(ACTIVE) show the active set of cell identifiers (CID) and sector identifiers (SID) with which the mobile station communicated during the call. Multiple entries in this set indicate a soft handoff state between sites or sectors during the call. We observed as many as 6 entries in the soft handoff events in our traces.

The traces do not include information on the geographical location of the cell site, nor the amount of data transmitted. The high-level protocol events (UDP, TCP) cannot be determined from this type of trace. Nevertheless, the collected data provides useful information about user mobility.

For the purpose of user mobility modeling, we summarize the packet call attributes per user and per cell site to obtain the following measurements:

- Number of packet calls per user and per cell site,
- Number of unique originating cell sites per user,
- Number of originating cell site changes per user, and
- Proportion of calls from each unique cell site per user.

We use the collected measurements to determine parameters for the user mobility model, as discussed in the following sections.

4. TRAFFIC DATA ANALYSIS

This section presents the results obtained from the traffic traces, including the statistical distributions of parameters to be used in the user mobility model for simulation.

4.1 High-Level Overview

Our analysis uses a week-long trace collected between 5:54 am on 25 March 2004 and 4:21 am on 1 April 2004. A total of 4,156 users were active during this period, placing 171,318 packet data calls from 139 cell sites. The averages are 41 calls per user and 1,232 calls per cell site.

4.2 Network-Level Mobility Analysis

To explore mobility for each user, we record the originating cell CID for each call in the trace, and count the number of changes in CID between successive packet calls by that user. The number of cell site (location) changes indicates the movement of the user between calls and thus represents their mobility level. Movement during a call is represented by soft-handoff states, but this data is inconclusive because most calls have short durations (5-12 seconds). We thus limit our investigation to the originating cell changes.

The number of cell site changes per user is plotted in Figure 2. The users are ranked according to their mobility level represented by the count of cell site changes. The skewed distribution indicates that a few users are very mobile, while many users have low mobility.

The shape of the distribution suggests heavy-tail behaviour. A distribution is said to be heavy-tailed if the asymptotic shape of the distribution is hyperbolic. In mathematical terms:

$$P[X > x] \sim x^{-\alpha}, \text{ as } x \to \infty, \text{ where } 0 < \alpha < 2$$

The parameter α, referred to as the tail index, determines the heaviness of the tail of the distribution. Smaller values of α represent heavier tails (i.e., more of the "mass" is present in the tail of the distribution).

To illustrate the heavy-tailed property more clearly, Figure 3 presents an analysis using the *aest* tool developed by Crovella et al [5]. The *aest* tool estimates the tail weight α for a heavy-tailed distribution. The graph shows a log-log complementary distribution (LLCD) plot of the cell site changes per user, with probability on the vertical axis, and users on the horizontal axis (each with log scale, and appropriately normalized [5]). The lowest curve in this plot shows the results for the raw data, while the successively higher curves show the results for the aggregated data, using a factor of 2 for each level of aggregation. The consistent slope of the plot over 5-6 levels of aggregation suggests the presence of a heavy-tailed distribution. The black dots on the curves indicate the points used to estimate the slope, which is α = 1.022 in this case. This α value indicates a heavy-tailed distribution, since $\alpha < 2$.

Despite the tail to the distribution, the general level of mobility in the network is low. In fact, 55% of the users are stationary, and 9.6% had only a single location change during the week. However, the top 10% mobile users account for over 63% of the total packet calls in the network; provisioning for their satisfactory mobile experience is important for a cellular provider.

Although highly mobile users contribute much to the overall network activity, this does not imply that stationary users make

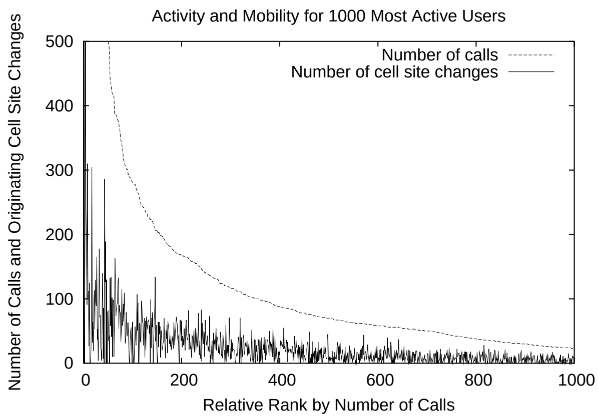

Figure 4: User mobility is weakly correlated with user activity level.

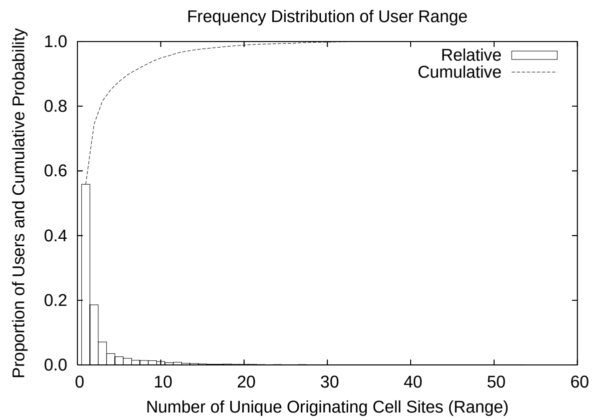

Figure 6: User roaming range suggests heavy-tail distribution.

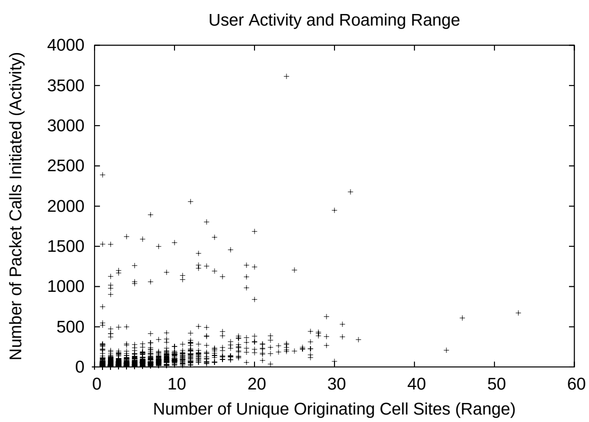

Figure 5: Users can be categorized by roaming range and activity level.

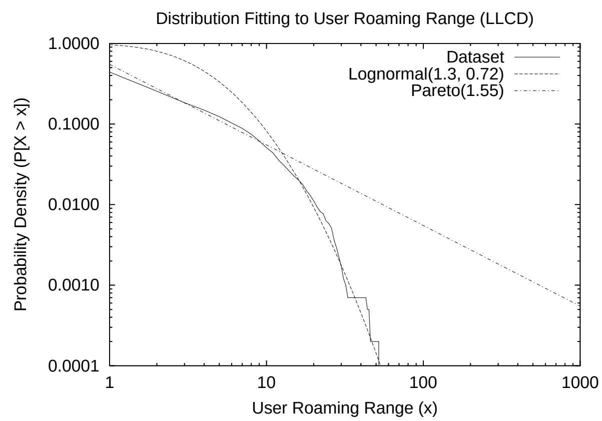

Figure 7: Hybrid distribution fit of roaming range (Pareto body and lognormal tail).

few calls. Rather, the level of call activity varies widely for both stationary and mobile users.

As shown in Figure 4, user mobility and call activity level are rather weakly correlated. The plots show the number of packet data calls made by each user (top line), and the number of cell site changes (bottom line) that occurred for that user during the trace, for the top 1,000 users sorted by activity level. The stationary users (i.e., those with 0 cell site changes) are scattered across the full range of call-level activity observed. This observation suggests that call activity level and cell site changes can be modeled as orthogonal characteristics in a user mobility model.

Another indicator of user mobility is the roaming range. We define roaming range as the number of unique cell sites that a user visits during the trace. While many location changes indicate frequent movement between calls, the roaming range indicates the total area of the network that a user covers. This number does not directly represent geographic distance, but does provide an approximation thereof.

Figure 5 uses a scatter plot to show the per-user roaming characteristics. Each point on the plot represents one user. The vertical axis shows the number of calls placed by the user, while the horizontal axis shows the number of distinct cell sites from which those calls occur.

There is little structure to this distribution, suggesting that call activity level and the number of cell sites visited are weakly related. However, there are arguably several different types of roaming patterns that can be discerned. One group (the dark band) represents low-activity clients with moderate roaming range. Above this band is a set of high-activity users with moderate range. At the very right are users with extreme range and mobility (over 30 visited cells implies at least that many cell site changes, which puts the user among the top 5% movers). Near the origin are many low-activity users with no mobility at all.

Figure 6 shows the empirically observed distribution for the number of cell sites from which packet data calls are placed, on a per-user basis. As indicated previously, about 55% of the users are stationary. That is, all of their observed calls are from the same cell site. The remaining 45% of the users are mobile, placing packet data calls from more than one site. One user placed calls from 53 different cell sites, suggesting a skewed tail to the distribution.

Figure 7 presents an analysis of the tail of the roaming distribution, to check for a heavy-tailed property (e.g., Pareto).

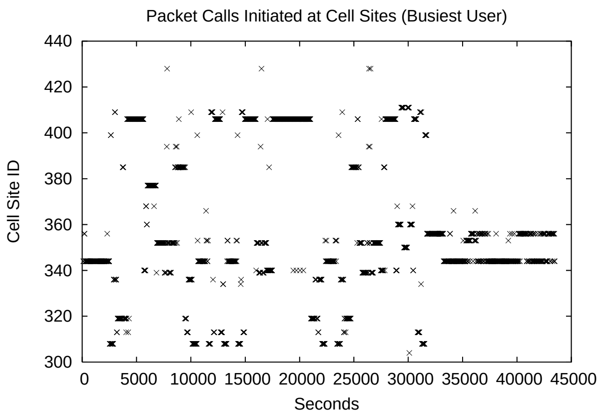

Figure 8: User places most calls from its "home cell".

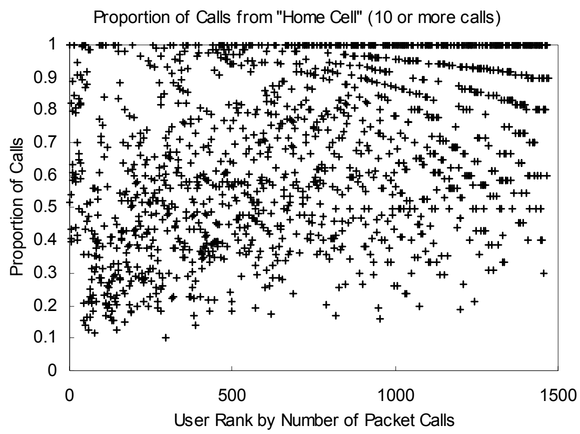

Figure 9: Scatter plot of "home cell" ratios shows spread across all levels of activity.

The results show that the aggregate distribution is not heavy-tailed, both graphically and using the *aest* tool. Rather, a lognormal distribution captures the tail behaviour quite well.

4.3 User-Level Mobility Analysis

The next analysis studies the mobility pattern of one particular user, namely the busiest user in the trace. This user makes over 3,000 packet data calls during the trace. Figure 8 shows a time series plot illustrating the originating cell site for each of this user's calls over a 12-hour period. Each X on the graph represents the arrival time of a packet data call.

Several observations are evident from Figure 8. First, this user originates packet data calls from over a dozen different cell sites. Second, the packet call activity of the user is bursty, with spurts of on/off behaviour. Analysis over longer time scales (not shown here) also illustrates on/off behaviour (e.g., overnight). Third, as might be expected, many of the calls appear in "clumps" with respect to cell sites, representing continuity to the session activity and the physical location of the user. Fourth, there seems to be one or two dominant cell sites for this user, from which a majority

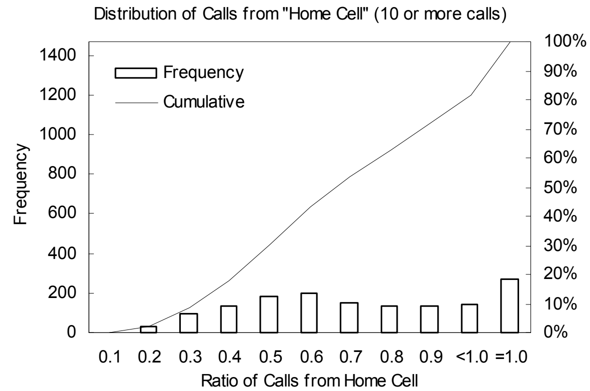

Figure 10: Histogram suggests that majority of users have a "home cell".

of the calls are placed. We refer to the dominant cell site as the "home cell" for the user, though we do not know whether this represents the residence, workplace, or some other location frequented by the user. Finally, the close timing relationships seen occasionally between packet data calls placed at different cell sites implies physical proximity between the cell sites, which is often indicated as well by the soft handoff activity in the trace. These patterns provide some insight into the topological structure of the cellular network.

Building upon the observation about the single user's mobility patterns, we explore the "home cell" behaviour for users that made 10 or more calls in our trace (a total of 1,469 users). The notion of "home cell" refers to the cell from which a user makes a significant proportion of calls. We set this proportion at 0.5, although arguably it may be set to a lower value.

Figure 9 shows the scatter plot of "home cell" ratios (proportion of calls from the most dominant cell). The most dominant band is for stationary users, who have a ratio of 1, by definition. Overall, 70% of users have a ratio of 0.5 or higher. Users having a "home cell" are distributed across all levels of activity, again implying that the level of activity does not necessarily determine mobility or range.

We explore the "home cell" phenomenon in more detail using a histogram (Figure 10), constructed by categorizing the users using bins of width 0.1 according to the ratio of calls from a "home cell". About 30% of users lack the "home cell" behaviour, with less than 50% of their calls originating from the most dominant cell. However, the other 70% are either stationary (about 20% in "=1.0" bin) or have a dominant "home cell" (0.5 to <1.0 bins). The latter category of users indicates that although roaming, these users still concentrate their activity in one cell, which could be the actual home where they live, or the work site where landline phone is not available or convenient.

Overall, we can conclude that this network has a small proportion of truly mobile users that make data calls, and that most users have a dominant "home cell" from which they originate most packet calls. We speculate that the "home cell" is in fact at home, since the peak of activity is in the evening hours, when people are generally at home rather than at work.

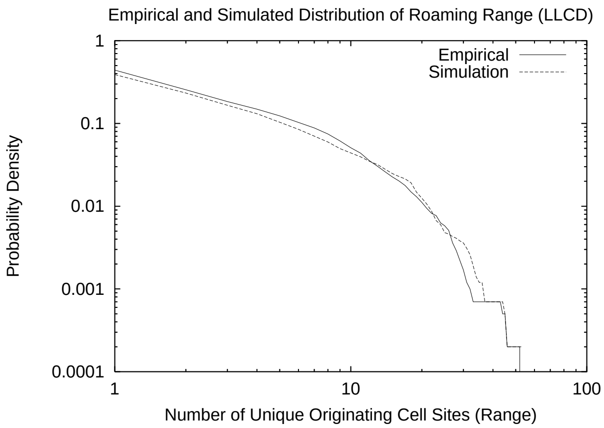

Figure 11: Simulated roaming range closely follows the empirical distribution in the body and tail.

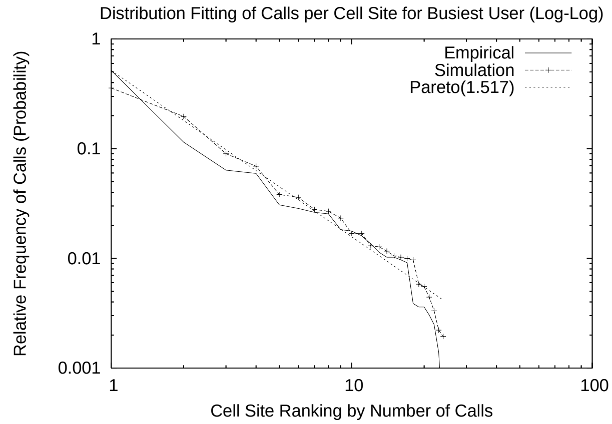

Figure 12: Pareto-modeled and simulated calls per cell site match the empirical data well except in the lower tail.

5. MOBILITY MODEL AND SIMULATION

We use both network-level and user-level mobility parameters in the model to capture the overall characteristics of the network. Using the foregoing results, we formulate parameters for the model and use them as input to the simulation.

A model for an event-driven simulation of the cellular network requires several basic parameters that capture single-user and overall network activity and mobility behaviour. In particular, we model the following:

- Number of calls initiated per user,
- Call inter-arrival time (IAT),
- Number of cell sites visited per user (roaming range),
- Number of user calls per cell site, and
- Probability of location change for the next call.

The number of calls initiated and the call IAT determine the user's activity level in the network. These values are external to our mobility model and are merely used as initialization parameters for the simulation. We do not focus on their generation in this paper.

5.1 User Mobility Model

We focus on three parameters that are directly relevant to user mobility modeling. These parameters capture the dynamics of single user mobility, i.e. continuity to the session activity with occasional trips outside the current cell and the existence of one dominant cell, as well as limited roaming for the typical user.

The distribution of roaming range (number of cells visited) per user is difficult to fit with a single distribution, as shown in Figure 7. We model a hybrid distribution composed of Pareto body and lognormal tail. The tail index of 1.021 is used for the body of the hybrid distribution, as obtained from *aest* tool, using only data for mobile users (excluding the stationary users). The parameters for the lognormal part are obtained in the same manner. We achieve a reasonably good fit, with some inaccuracy near the lower tail. Figure 11 shows the empirical and the simulated roaming range distributions.

Once the roaming range is assigned to the user, the next parameter is the distribution of calls to cell sites. We find that users distribute their calls over cell sites in a power-law fashion, based on the observed empirical data for a sample of busy users. The tail index is calculated as (1 + p), where p is the probability of calls being initiated from a user's "home cell" ("home cell" probability). For each user, the pre-generated set of cells is biased in probability of call assignment and used throughout the simulated number of calls for that particular user. The Pareto(1+p) fitting of the distribution of calls per cell site to the empirical, as well as simulated curve for the busiest user is shown in Figure 12. The visual match to the distribution is good.

The key component of our model is the "home cell" probability. The proportion of calls coming from the user's "home cell" can be reasonably well modeled using the distribution shown in Figure 10. We approximate this distribution by first separating the stationary users, using a constant probability of 0.55. For the other users we assign a "home cell" probability according to the Uniform distribution over the interval (0.2, 1.0). Users placing under 20% of the calls from the "home cell" are absorbed in other categories in the simulation, since they make up less than 5% of user population.

Finally, we need to represent the mobility level of users (number of location changes) in a simulation. It is not practical to model the number of location changes directly because this value must not exceed the number of calls. For the modeling and simulation, we express mobility as a probability of location change (c), calculated as the ratio of number of cell changes and total number of calls initiated by the user. This way the stationary users will have 0 probability of cell change.

Based on the distribution of c (Figure 13), we model the c value for each user as follows:

- P[c = 0.0] = 0.55 (user is stationary),
- P[c = Uniform(0.0, 0.1)] = 0.06,
- P[c = Uniform(0.1, 0.5)] = 0.35, and
- c = Uniform(0.5, 0.9) otherwise.

This is the only component of our model where we do not use a known statistical distribution. The empirical and simulated values

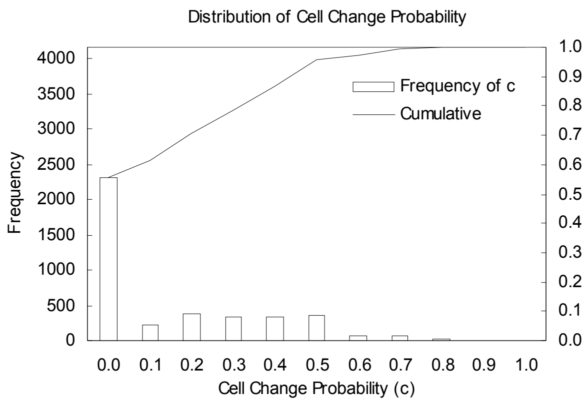

Figure 13: Distribution of cell change probability does not resemble any known distribution.

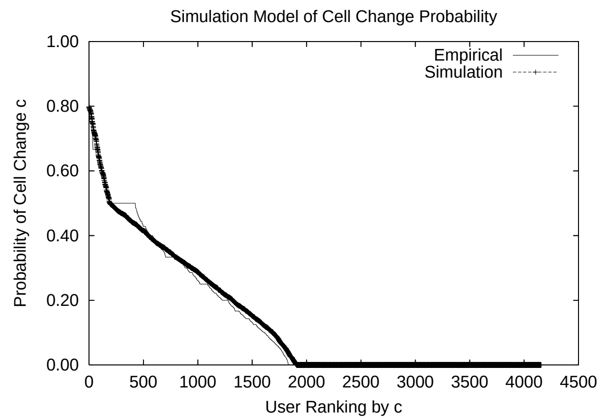

Figure 14: Simulated cell change probability closely follows the empirical data.

of c are compared in Figure 14. The leftmost part of the model fits well for highly mobile users, while the rightmost half fits well for the stationary users. The middle piece shows a very close fit, but the model underestimates the number of users with c = 0.5. Many of these users in the empirical data had only two calls.

5.2 Model Validation

To validate the model for each parameter we run 10 single-user simulations and compare the parameter distribution plots, call time-series plot, number of location changes, and number of cell sites visited to the empirical results. We find that the call distribution across cells covers the roaming range accurately. The average number of cell changes over the simulations also matched well with the specified value.

Finally, we show an example single-user call simulation in Figure 15. The graph shows a time-series plot of calls for the busiest user, using the empirically obtained parameters as inputs to the simulation. The cell IDs are ordered by call count with 0 marking the "home cell". The simulated user behaviour is representative of the empirical mobility behaviour (see Figure 8). The on/off periods are present and the dominant "home cell" is clearly seen, as well as session-like clumps of calls from cell sites. This simulated user visited 24 cell sites and made 736 location changes in the trace. These results represent a highly mobile user.

6. SUMMARY AND CONCLUSIONS

This paper presents the analysis of data call traces from a CDMA2000 1x cellular network, and building of a user mobility model suitable for simulation studies. The analysis focuses on a one-week portion of the trace during which 4,156 users initiated 171,318 packet data calls from 139 cell sites of the network.

The results from our traffic analysis indicate heavy-tail characteristics in user mobility profiles, as well as low overall mobility and low roaming range. Similar characteristics are found in earlier studies of wired and wireless data traffic, and we can now apply them to user mobility in cellular networks. We further find that both mobility level and roaming range are weakly correlated to the level of call activity. A notion of "home cell" is introduced, based on the observation that many users originate calls from one dominant cell site regardless of the level of call activity.

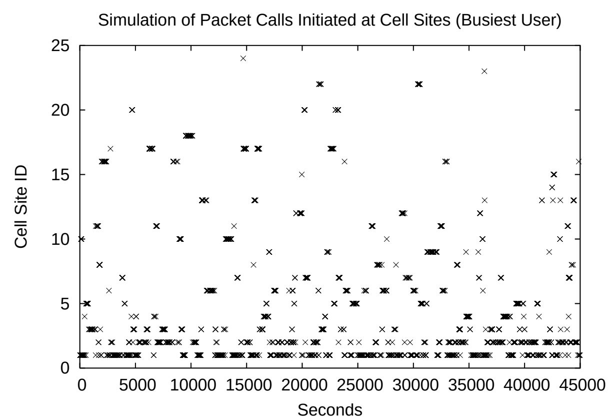

Figure 15: Simulated calls capture user mobility patterns.

We develop a user mobility model based on the empirical findings and use it for simulation of individual user mobility properties in the cellular network. Although several model parameters are not easily represented by standard distributions, we achieved a simple and practical model for our simulation purposes. The model is validated against our empirical data.

We expect that the findings from this study will benefit researchers studying next generation cellular networks, as well as cellular providers provisioning networks for their users. Our further work will focus on refining the mobility model, as well as simulating the application-level protocols in cellular networks (WAP, WWW, email, etc.).

7. ACKNOWLEDGEMENTS

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