An Empirical Study of a Highly Available File System

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Abstract

In this paper we present results from a six-month empirical study of the high availability aspects of the Coda File System. We report on the service failures experienced by Coda clients, and show that such failures are masked successfully. We also explore the effectiveness and resource costs of key aspects of *server replication* and *disconnected operation*, the two high availability mechanisms of Coda. Wherever possible, we compare our measurements to simulation-based predictions from earlier papers and to anecdotal evidence from users. Finally, we explore how users take advantage of the support provided by Coda for mobile computing.

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1. Introduction

Providing *high availability* is a dominant theme of current file system research. Examples of systems with this goal include Coda[18], Echo[6], Ficus[14], HA-NFS[2], Deceit[22], and FACE[3]. Now that serious use of such systems is feasible, it is appropriate to ask how well their high availability mechanisms function in practice. This paper is our attempt to answer this question for the Coda File System. To the best of our knowledge, this is the first empirical study of a highly available distributed file system.

Empirical studies of file systems have a long history, stretching back to the 1970s. Early studies of timesharing file systems such as those by Stritter[26], Smith[23], Satyanarayanan[15, 16], Ousterhout[13], and Floyd[4, 5] formed the basis for our initial understanding of file system usage. This understanding was crucial to the design of distributed file systems such as AFS[7] and Sprite[12]. In 1991, Baker et al.[1] examined Sprite with a view to establishing how closely its real usage matched predicted usage. More recently, Spasojevic and Satyanarayanan[24] reported on the use of wide-area AFS.

In this paper, we report on data collected from Coda over a 6-month period. During this time, Coda was relied on daily by a community of almost 40 users. Our data shows that failures do occur in practice, and that Coda's high availability mechanisms are effective in masking them. We establish that users do take advantage of Coda's high availability mechanisms, and that the resource overhead of these mechanisms is modest under conditions of real use.

Our paper begins with a brief overview of Coda. We then discuss the factors that influenced our data collection strategy and present its design. The bulk of the paper is a presentation of our measurements. Wherever appropriate, we point out ways in which these measurements corroborate or contradict simulation predictions and anecdotal user observations. We conclude with a brief summary of results.

2. The System Studied

Coda, a descendant of AFS, was designed to offer continued access to data in the face of server and network failures. In this section, we provide a short overview of Coda; further details can be found in earlier papers[9, 11, 17, 18, 19, 20, 25].

Clients view Coda as a single, location-transparent shared Unix file system. The Coda name space is mapped to individual file servers at the granularity of subtrees called *volumes*[21]. At each client, a user level process, *Venus*, caches data on demand on the client's local disk. An in-kernel VFS driver[10], called the *MiniCache*, intercepts and forwards file references to Venus.

Coda uses two distinct, but complementary, mechanisms to achieve high availability. Both mechanisms rely on an *optimistic* replica control strategy. This offers a high degree of availability, since data can be updated in any network partition. The system ensures detection and confinement of conflicting updates after their occurrence, and provides mechanisms to help users recover from such conflicts.

The first high-availability mechanism, *server replication*, allows volumes to have read-write replicas at more than one server. The performance cost of server replication is kept low by caching at clients, and through the use of parallel access protocols.

The second high-availability mechanism, *disconnected operation*, allows continued read and write access to cached data even when no server is accessible. Disconnections may be *involuntary* or *voluntary*. Involuntary disconnection typically occurs when there is temporary communication failure. Voluntary disconnection occurs when a user deliberately isolates a client from the network. This mechanism is especially valuable for mobile computing: a user may be isolated because no networking capability is available at the remote location, or to avoid use of the network for economic or power consumption reasons.

3. Measurement Strategy

In this section we first describe the key factors that influenced our measurement strategy, and then describe the data collection architecture that we developed to address these factors. We complete the section with a description of the hardware and user environment in which our data was collected.

3.1. Considerations

A dominant factor influencing the design of our data collection was the desire to study the system over a long period of time. Such a long-term study is valuable because our user community is expected to grow, thereby increasing the diversity of use of the system. Further, mobile computing is a new mode of interaction, and people's use of the system may change as they grow more familiar with it, and as the portable computers on which Coda runs improve.

Long-term data collection makes it likely that what is collected may have to change over time. Because Coda is a system undergoing active development, appropriate refinements to the instrumentation will be necessary as new functionality is added and improvements are made. Other changes to the instrumentation may be warranted by our own improved understanding of the system based on early measurements.

These considerations have two implications. First, the data collection mechanism has to be flexible and easy to administer. Second, the data analysis software has to cope with data collected over a very long time, spanning many different versions.

Another major factor influencing our design is the need to minimize the impact on users. Data collection should not require active intervention by users, especially in a long-term study. Nor should it degrade performance or reduce availability noticeably; otherwise, users may alter their behavior to cope with these shortcomings.

A final factor in our design was the need to avoid losing data in spite of the wide range of failures experienced by clients and servers. A particularly challenging problem was to extend the data collection to voluntarily disconnected portable machines that might not be reconnected to the network for many days.

3.2. Measurement Framework

Figure 1 illustrates the data collection architecture that we developed in response to the concerns described in the previous section. Both Coda clients and servers are instrumented. The data they collect is shipped to a central data collector, which spools it to a log on disk. Once a day, a reaper process reads this data and inserts it into a relational database. This two-stage collection process removes the database from the critical path of data reporting by clients and servers.

Data collection is subject to a wide range of failures. For example, the data collector may be down for hardware or software reasons. A client or server may fail, causing buffered data to be lost. There may be a network outage that prevents a subset of the clients and servers from contacting the data collector. An especially common form of network outage in Coda is the voluntary disconnection of a portable computer, sometimes for days.

We provide robustness in the face of such failures through two buffering strategies. On servers and connected clients, we buffer the data in volatile memory and periodically flush it to the data collector. The frequency of flushing, currently two hours, is a compromise between minimizing lost data and reducing collection overhead. If the collector is down, servers and clients retain data until a future flush succeeds. On disconnected clients, which may be turned on and off many times before reconnection, we buffer collected data in non-volatile storage until reconnection. We use the *recoverable virtual memory (RVM)* transactional mechanism for this purpose because of its clean failure semantics[20]. Since RVM resources are precious on a resource-poor portable computer, we strictly and conservatively cap its usage; this favors availability of the system over completeness of the data collected. In combination, these robustness mechanisms have proved to be quite effective – in our experience, the number of occasions on which we have lost data has been negligible.

Our architecture minimizes the performance impact of data collection on clients and servers. We summarize data at the clients and servers whenever doing so is inexpensive and results in minimal loss of information. Such summarization reduces the total amount of data that must be stored as well as the burden of shipping data. The collected data is only processed offline, after it resides in the database.

We emphasize flexibility throughout the data collection process. The bulk of the data collector's implementation is independent of the specific data being collected. When changes are made to a data type, only a small portion of the collector needs to be recoded. When the data collected is changed, we ensure that only upgraded clients and servers are able to report data; all others are rejected with an advisory message. Thus, both system administrators and users soon learn of obsolete clients and servers. This is important because it would be administratively difficult to atomically update all nodes, especially where some of them may be disconnected.

Our use of a relational database as the permanent repository of collected data provides us with an open-ended mechanism for framing questions long after the data has been collected. It also provides us with a scalable tool for storing and manipulating large quantities of data at a fine granularity. By including version information with the data and in post-processing queries, we are able to cope with multiple generations of data.

3.3. Coverage

Our data collection took place in a system with 40 clients, of which 15 were portable machines. There are 39 user accounts, roughly 25 of which are used regularly. The user community is comprised of Coda developers as well as other computer science researchers. There are 10 file servers, organized as one triply-replicated set of production servers, one triply-replicated set of beta test servers, and four independent alpha test servers. Each production server holds almost 1.4 GB of data, while each of the beta test servers holds about 1.1 GB. Data on both the production and beta servers are regularly used by our entire user community. Alpha test servers are only used by Coda developers.

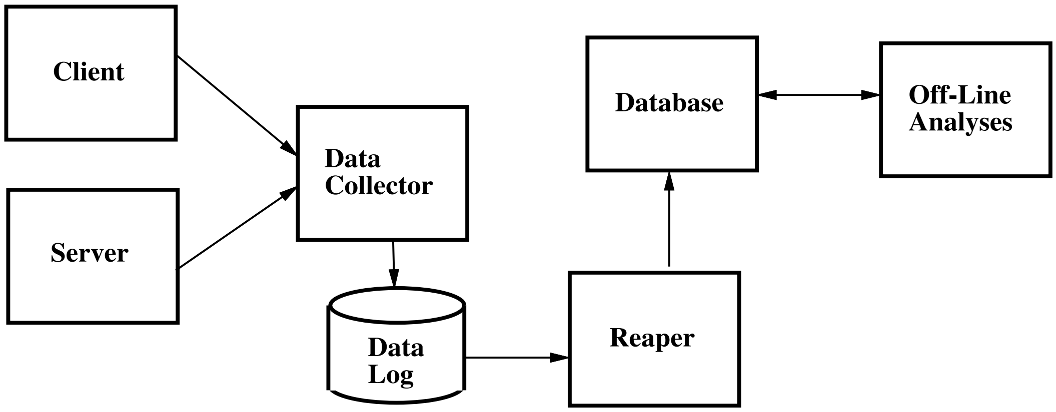


Figure 1: Data Collection Architecture

Data collection began in March 1992. There was an initial test period lasting 6 months, after which the data was analyzed and the collection software revised. Another revision was made 10 months later, based on the results of a second test period. The data presented in this paper corresponds to the third major revision of our collection software. This collection began in July 1993, and covers a period of six months[1]. Where appropriate, we highlight data that has changed significantly since this paper was submitted for publication. That data covered only the first three months of this study.

4. Results

We present our observations as answers to a set of questions that reflect on the high availability aspects of Coda. Our discussion begins in Section 4.1 with a characterization of observed failures. We ask, "How often are service failures experienced by the system?" We then address the question, "How successful is Coda in masking these failures?"

Next, in Sections 4.2 and 4.3, we examine the two Coda mechanisms that mask failures: server replication and disconnected operation. For each we ask, "How well does this mechanism work?" and, "How expensive is this mechanism, in terms of resources consumed?"

Finally, in Section 4.4, we ask, "Is voluntary disconnected operation used as anticipated?" Since voluntary disconnected operation is a new model of computing, we would like to better understand it from the user's perspective.

[1] An exception to this is the data presented in Section 4.2 on resolution. The instrumentation for this data is more recent, and the data was only collected for four months.

4.1. Profile of Failures

We characterize observed service failures in Coda in three steps. First, we classify the set of failure states based on their severity. Next, we examine the longevity of those states. Finally, we show how data access degrades in each of the states.

4.1.1. Volume Connectivity

As we noted in Section 2, the Coda name space is broken into subtrees called volumes. Each volume is stored on a set of servers, known as that volume's *volume storage group (VSG)*. At any point in time, a client can contact some subset of the VSG known as the *accessible volume storage group (AVSG)*.

We classify the connectivity of volumes based on the ratio of AVSG size to VSG size, as seen by each client. Note that different clients may be in different states of connectivity with respect to the same volume. A volume whose AVSG is equal to its VSG is *fully connected*. A volume whose AVSG is empty is *disconnected*. All other volumes are *partially connected*.

We draw a distinction between two types of partial connectivity. If a volume's AVSG is larger than half its VSG, it is *majority connected*. Otherwise it is *minority connected.* An optimistic replication scheme is necessary to provide read/write access to volumes that are minority connected or disconnected. Either an optimistic or a pessimistic scheme can provide read/write access to majority or fully connected volumes.

Table 1 shows the amount of time, weighted by volume usage, clients have spent operating in varying levels of

Failure State	Percent of Time
Fully Connected	92.3%
Majority Connected	4.4%
Minority Connected	1.2%
Disconnected	2.0%

Table 1: Distribution of Failure States

connectivity. Optimistic replication was essential over 3% of the time. The high availability mechanisms as a whole were necessary nearly 8% of the time. Our environment has also become more stable over the past three months; these percentages were much higher over the first half of this study.

4.1.2. Longevity of Failure States

Associated with each volume on a client is the notion of the current *session*. A session is defined as the maximal period of time over which the AVSG for the volume does not change. Each change in connectivity between a client and a server ends the client's current session for each volume stored on that server, and begins a new one.

We divide sessions into two categories, *transient* and *non-transient*. We consider sessions that are less than 15 minutes long to be transient. These sessions are typically due to network glitches. They may also be due to the gradual detection of a partition between a client and several servers. We chose 15 minutes because it was the smallest number that clearly exceeded the typical durations of transient events recorded in our data. It is also under the minimum server restart time. Of the sessions we have observed, 54% of them have been 15 minutes or less. However, these short transient sessions account for only 1% of the total observed time.

Figure 2 shows the distribution of the lengths of non-transient sessions. Fully connected sessions, shown in Figure 2(a), are the most common and tend to be longest-lived. These sessions never last more than 22 hours because of our server restart policy. Each server is restarted every night so that consistency checks performed at startup can catch corruptions at most one day after they happen. The shutdown times are staggered to reduce the likelihood of complete disconnection.

Since all of our servers are located in the same room, partial connectivity is due to server, not network, failure. Figure 2(b) shows that partially connected sessions are mostly short. These short sessions often occur when a server fails and is quickly brought back on line. However, there are some sessions that lasted much longer; these stem from more serious problems befalling a server. The histogram for the complete six month study is more heavily skewed toward short server outages than that observed during the first three months.

Disconnected sessions, shown in Figures 2(c) and 2(d), also tend toward shorter durations. Many of these short periods correspond to network partitions. Some of the periods correspond to occasions when all servers crash due to operator error, power failure, or software bugs. These short disconnections are instances of involuntary disconnection.

Most of the longer session lengths in Figure 2(c) are due to voluntary disconnections. Users sometimes work at home on their laptops, and often take them along on extended trips. As Figure 2(d) shows, some of these voluntary disconnections can last many days. The longest recorded disconnected session was over four days in duration. Many of our users have actually operated on their laptops away from the network for even longer periods. However, those longer periods have involved powering down their laptops, thus resulting in multiple sessions rather than one long session.

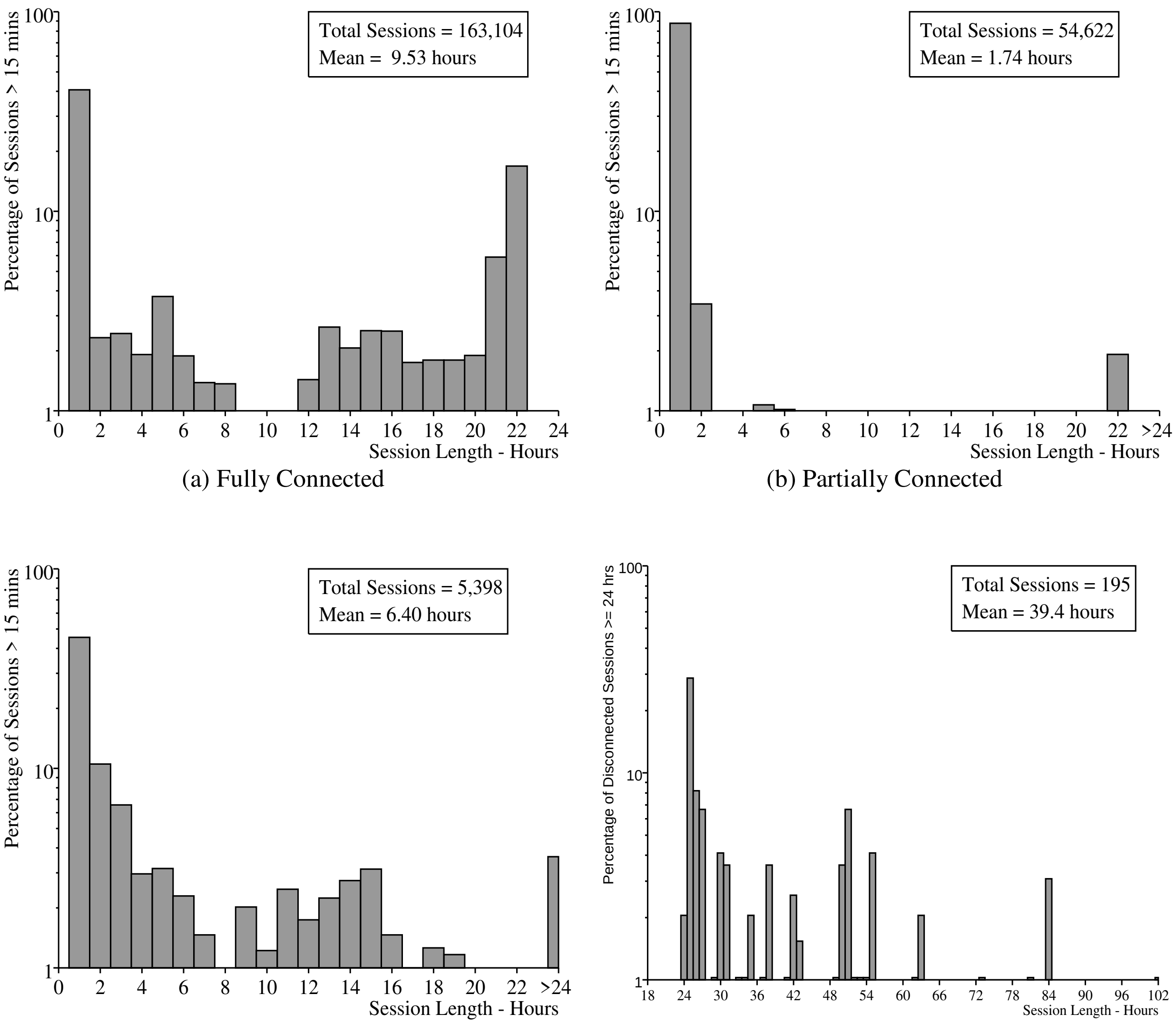
4.1.3. Masking Failures

How do these failures affect a client's ability to satisfy file requests? We estimate this by measuring the change in failure rates of the most frequently occurring file system operations on clients during various states of connectivity. Note that operations can fail even when fully connected because of application or user errors, or by programs like the shell probing search paths for system binaries.

Table 2 compares the success rates for the most frequent operations at clients for various states of connectivity. For the `getattr`, `access`, `open`, and `close` operations, degraded connectivity hardly affects success rate.

At first glance, the data for `lookup` seems anomalous. In all states of connectivity, its success rate is the lowest of all operations. This is partly because a `lookup` typically precedes other operations on an object; failure of the `lookup` suppresses the later operations. Compounding this is the fact that the data for Table 2 is collected after the MiniCache has filtered out many successful `lookups`[25]. Combined, these two factors account for the high observed failure rate of `lookup`.

The message of Table 2 is that as connectivity degrades, the success rates of operations barely decline. In other words, the user does not experience a corresponding increase in failures. This confirms that Coda does indeed provide high availability of data in the face of service failures.



(a) Fully Connected

(b) Partially Connected

(c) Disconnected

(d) Disconnected — 24 hours or longer

This graph shows the distribution of the lengths of sessions, a per-volume concept as discussed in Section 4.1.2. Each histogram bucket contains the number of sessions longer than the bucket below, but less than or equal to the number of hours of the x coordinate. The last bucket in Figure 2(c) contains all disconnected sessions greater than 23 hours in duration; the graph in Figure 2(d) shows the distribution of only those sessions. Note that only sessions longer than fifteen minutes were included in these histograms, accounting for 99% of observed client operation. Also note that the y axes are $\log_{10}$ scaled.

Figure 2: Longevity of Non-Transient Sessions

Operation	Fully Connected	Majority Connected	Minority Connected	Disconnected
`lookup`	58%	75%	94%	86%
`getattr`	>99%	>99%	99%	>99%
`access`	99%	99%	>99%	99%
`open`	>99%	>99%	>99%	99%
`close`	>99%	>99%	>99%	>99%

This table shows the success rates of the five most common operations seen by Venus. Connectivity decreases from left to right in the table. The consistently lower success rates for `lookup` are explained in Section 4.1.3.

Table 2: Operation Success Rates by Connectivity.

Note that this analysis does not take into account the secondary effects of failures upon the file references generated by a user. For example, not being able to open an editor will result in only one error reflected in our data, but this failure will prevent the user from generating those references that would have resulted from use of the editor. Unfortunately, we know of no way to quantify such secondary effects of service failures. Anecdotal evidence suggests that once users become proficient at *hoarding*, the process of advising Venus which files should be cached, such task-disabling failures are rare.

4.2. File and Directory Resolution

Replicas in Coda may lose coherence because of update activity during server or network failures. *Resolution* is the process of restoring coherence to all replicas of an object. In the vast majority of cases, resolution merely involves overwriting a stale replica with the most current one. However, because Coda uses optimistic replication, more than one replica of an object may have been updated during a partition. In the case of directories, many such instances of divergence can be resolved automatically by the system. All other instances of divergence, whether file or directory, result in resolution failure, with the replicas being marked in *conflict*.

In this section, we ask how often resolution is invoked and how often it succeeds. When directory resolution results in conflict we examine the causes of failure. Since directory resolution is based on an *operation logging* strategy, we also ask how much log space is consumed. We then compare our observations with earlier predictions of log growth based on trace-driven simulation.

4.2.1. Frequency and Outcomes of Resolution Attempts

Our measurements show an average of one resolution request per volume per client every five hours. Table 3 shows the results of resolutions we have measured. The table shows that resolution succeeded over 98% of the time, requiring virtually no work in many cases. These situations corresponds to *weak equality,* where the replicas are actually equal, but their version information does not reflect this fact. The circumstances under which this can happen have been explained elsewhere[18]. Another common event is *runt forcing*. This corresponds to situations where an empty file replica was created via a previous resolution of the parent directory.

As shown in the table, there were 21 directory resolution attempts that had to be aborted due to our deadlock avoidance policy. These attempts are neither successful nor result in a conflict.

	Files	Directories
Attempts	3,761	3,009
Successes	3,721	2,934
Weakly Equal	717	2,288
Runt Force	2,410	NA
Other	594	646
Conflicts	40	54
Deadlock Avoidance	NA	21

This table shows the results of file and directory resolutions observed by our collection software. For successful resolutions we further classify our data into simple resolutions ("weakly equal" and "runt force"), and more complex ones ("other"). Note that runt forcing does not apply to directories. We also show, for directories, how many resolution attempts could not proceed due to our deadlock avoidance policy.

Table 3: Resolutions

Table 3 indicates a conflict rate of about 1.3%, only slightly larger than that predicted by an earlier study based on AFS[9]. This discrepancy is partially due to limitations in our implementation of directory resolution, as elaborated in the next section.

4.2.2. Causes of Directory Conflicts

An attempt to resolve a directory can fail for two classes of reasons: *semantic conflicts*, arising from true non-serializability, and *spurious conflicts*, arising from limitations of our current implementation. Table 4 details reasons for directory conflict as observed at individual replica sites participating in a resolution attempt. Since these observations must be made at the replica sites themselves, as opposed to the resolution *coordinator*[11], they give an upper bound on the total number of conflicts. For example, suppose client A updates file `foo` on replica A, and client B updates the same file `foo` in on replica B, which is partitioned from replica A. When the partition is healed, both replica A and replica B will record a conflict, when only one semantic conflict is present.

Semantic conflicts can be further classified into *name-name*, *remove-update*, and *update-update* conflicts. A name-name conflict arises when objects with the same name are created in a directory in different partitions. The removal of an object in one partition, and its update in another, results in a remove-update conflict. An update-update conflict results when the same object is modified in different partitions. The observed number of each of these types of conflicts is presented in the left hand column of Table 4.

There are three implementation limitations leading to spurious conflicts in Coda. First, resolution of cross-directory

Semantic Conflicts	Count	Spurious Conflicts	Count
Name-Name	24	Rename	26
Remove-Update	12	Log Wrap	26
Update-Update	6	Propagation	0

This table shows the breakdown of causes for directory resolution failures. The left hand column shows semantic conflicts, arising from non-serializability; the conflicts listed in the right hand column arise from limitations in our current implementation. These conflicts are not mutually exclusive, and are upper bounds on the number of actual conflicts due to our instrumentation methodology. Hence, the sum of the numbers in this table may exceed the number of failed directory resolutions reported in Table 3.

Table 4: Conflict Types Observed by Replicas

renames is not currently supported. Second, resolution logs are of finite length and may wrap-around during long partitions with intense update activity. Third, propagation of a previously detected directory conflict to newly accessible replicas is counted as a separate conflict by our accounting mechanism. The right hand column of Table 4 shows the observed impact of each of these limitations.

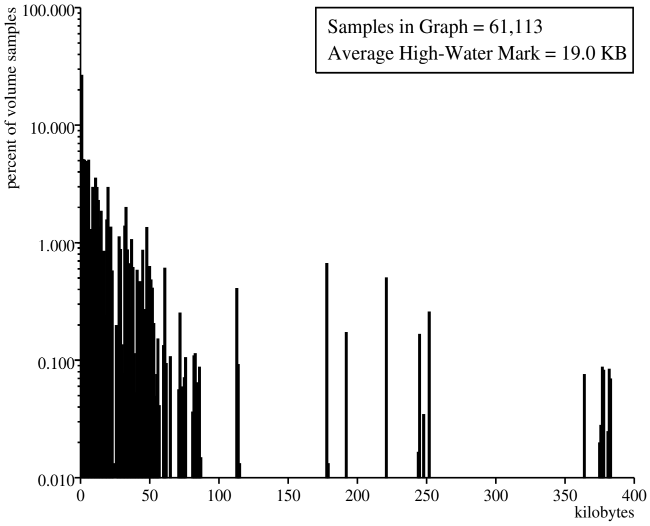
4.2.3. Size of Directory Resolution Logs

Since Coda uses a log-based approach to directory resolution, it is important to ask how much space is consumed by these logs in practice. Figure 3 shows the distribution of maximum size, or *high-water mark*, attained by each volume's log each day. The figure indicates that log growth is quite modest, with a mean high-water mark of 19KB. Although a few instances of high-water marks over 250KB were observed, the vast majority were under 200KB.

A previous study, based on trace-driven simulation of the resolution subsystem [11], predicted a maximum log-growth of 3.3MB per volume per day. Our observations indicate that this grossly overestimates true log growth – the largest value we have observed is 385KB per volume per day. That study also predicted that 99.5% of all resolution logs would grow less than 240KB per day. This is completely consistent with the results in Figure 3 which indicate that over 99% of all operation logs grow less than 240KB per day.

4.3. Disconnected Operation

Mutations made during disconnected operation at a Coda client are recorded in a per-volume *replay log*. Coda employs many *cancellation optimizations*[8] to reduce the amount of log space used. Upon reconnection, the client transparently invokes *reintegration* of each modified volume. If a volume's



This graph shows the distribution of the maximum resolution log size reached each day by each volume. The high-water mark is reset each morning to the current log size. Note that the y axis is $\log_{10}$ scaled.

Figure 3: Daily High-Water Marks of Resolution Log Sizes

log is successfully replayed by the servers, they proceed to *backfetch* the contents of modified files. If replay fails, the log and associated files are saved in a *closure*, for the user to inspect and replay manually.

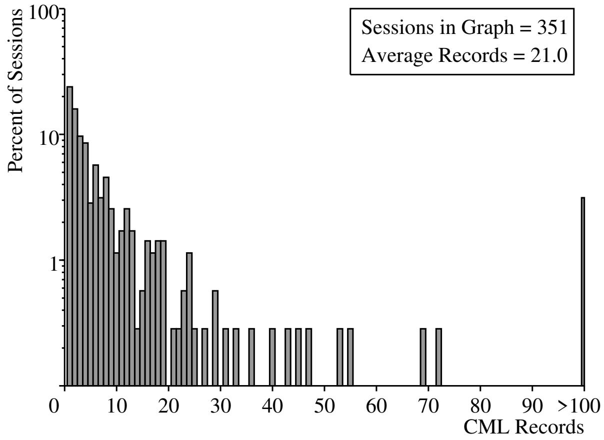
In this section, we ask how large replay logs become, and how effective the optimizations are in reducing log growth. We also examine the outcomes of reintegrations and their latency.

4.3.1. Size of Replay Logs

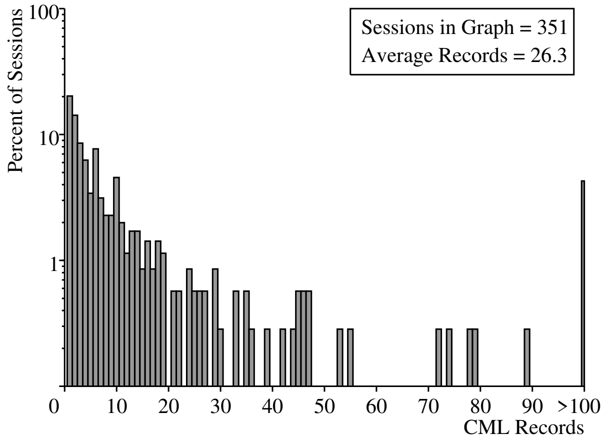
Figure 4(a) shows the observed replay log sizes at the end of the corresponding disconnected sessions. The distribution is skewed toward the low end, and has a mean of 21 records. This reflects a much greater use of the system than observed in the first half of this study where the mean was just over half that; in other words, more data is mutated while disconnected. The distribution has a long tail, with a maximum value of 1,466 records.

The high-water mark of a replay log's length could be different from its final length because of explicit deletion of objects created during that session. Such a deletion eliminates all earlier log records for the object. Figure 4(b) shows the distribution of observed high-water marks. As expected, this distribution is shifted to the right of Figure 4(a), with a mean of 26.3 records.

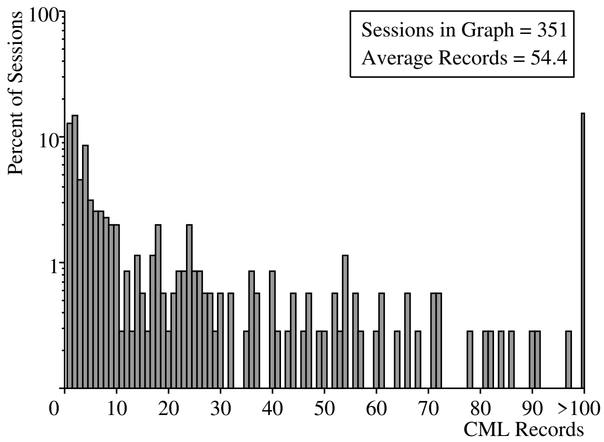
Log optimizations prove to be very effective. Figure 4(c)



(a) Records at End of Session



(b) Record High-Water Mark



(c) Records Without Optimizations

These graphs show the distribution of replay log sizes under various situations. Figure 4(a) shows log sizes at the ends of disconnected sessions. Figure 4(b) shows the distribution of log high-water marks. Figure 4(c) shows what log sizes would be without optimizations.

Figure 4: Replay Log Lengths

Attempts	461
Successes	400
Log Records Committed	6,666
New Files Created	1,290
MB Backfetched	176
Failures	61
Confirmed Server Disappearances	14
Log Records Saved in Closures	89

This table shows the breakdown of reintegration results, as well as details of successful and failed reintegration. For successful reintegrations we show the total number of log records committed, how many of those log records were creations, and how much data was backfetched by the servers. For failures, we give the number of log records that were saved in closures. We also give the number of failed reintegrations that are known to be due to server or network failure rather than for semantic reasons. There is one anomalous case not included in these figures; it is explained in Section 4.3.2.

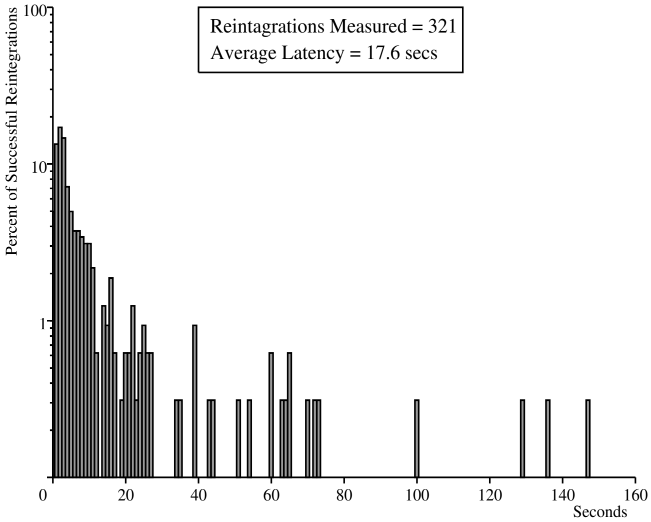
Table 5: Reintegrations

shows the distribution of lengths that the logs would have reached had optimizations not been applied. This distribution is substantially shifted to the right of Figure 4(a). On average, replay logs without optimizations would have been over 2.5 times longer than the logs actually encountered in Coda. This corroborates earlier estimates, based on trace-driven simulation, that indicated that unoptimized logs would be between 2 and 3 times the length of optimized logs[19]. This result is also consistent with anecdotal evidence from our users, who claim to often work disconnected on a small set of files, but overwrite them frequently.

4.3.2. Reintegration

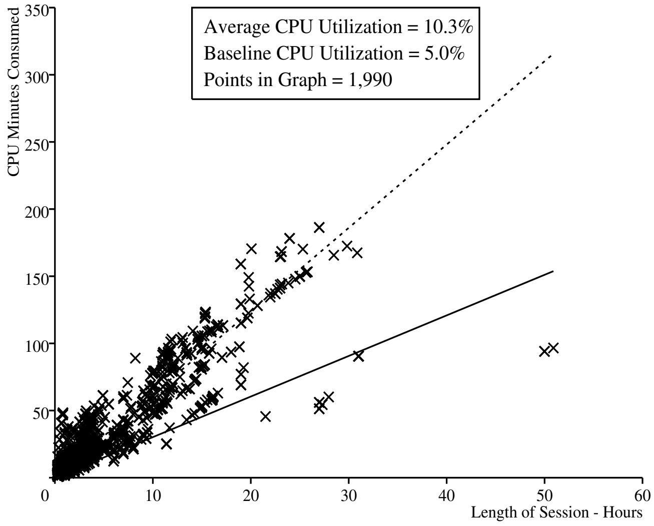
Table 5 shows a summary of the reintegration attempts in data volumes we have seen so far; we do not include numbers from test volumes. Over 85% of all reintegration attempts succeeded. On average, each successful reintegration involved replay of just over 16 records and backfetching of about 450KB of data. Since most of these reintegrations were to triply-replicated data, the effective amount of new data created during a disconnected session is at least 150KB.

The high number of failed reintegrations was initially surprising to us, because it contradicted anecdotal evidence that users rarely experience reintegration failure. From our raw data we are able to confirm that almost one quarter (14 out of 61) of the reintegration failures are due to a server disappearing during reintegration. Some of the remaining 47 failures may also be attributable to this cause, but we are unable to confirm this. However, even if all 47 failures were due to conflicting updates, we conjecture that many would be due to multi-machine activity by the same user. As a result,



This graph shows the distribution of latencies measured at the client for successful reintegrations. As discussed in 4.3, this latency includes the time for replay at all AVSG members as well as the backfetching of file contents by them. There is one outlier not pictured here, as detailed in Section 4.3.2.

Figure 5: Reintegration Latency Distribution



This graph shows the laptop CPU consumption for disconnected sessions, a per-volume concept as discussed in Section 4.1.2. The dotted line represents the average number of minutes consumed per hour, deterimined by dividing total CPU usage by total elapsed time. The solid line represents the observed CPU consumption of an idle laptop which caches this paper, the data collection source code, and the X11, GNU Emacs, and TEXsoftware collections: a typical cache set in our environment.

Figure 6: CPU Usage During Laptop Disconnections

the high rate of reintegration conflicts would not *prima facie* contradict our earlier predictions of much lower likelihood of conflicts between different users[9].

One anomalous event is not included in the above analysis. A user who was unfamiliar with the write-sharing semantics of Coda ran simulations on five machines which logged information to a single Coda file. He was unaware that, unlike traditional Unix, Coda detects concurrent write-sharing and preserves the first and all later updates. This preservation is done by treating the later updates as failed reintegrations, and saving the data in closures. In this case, the simulations ignored failed reintegrations and pushed on blindly, causing 188 failed reintegrations over the course of one evening!

Figure 5 shows the distribution of observed reintegration latencies. The vast majority of reintegrations had latencies of ten seconds or less, though there are some outliers beyond 90 seconds. There was also one outlier at just over seven minutes; this data point was elided from the graph for readability, but is reflected in the mean. We conjecture that the outlier was due to repeated transient network failure. The low overall latencies corroborate our users' experience that most reintegrations are barely noticeable, contributing to the transparency of disconnected operation.

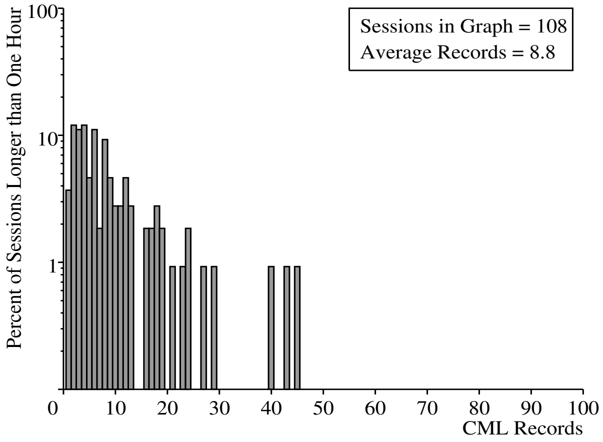
4.4. User Behavior While Disconnected

In this section, we ask how users take advantage of voluntary disconnected operation. We address this question in three ways. First, we examine the CPU consumption on disconnected portable computers. Second, we look at mutation activity during voluntary disconnections. Finally, we compare the VFS operation mix during connected sessions and voluntary disconnected sections.

Our data collection has no way of accurately recording whether a disconnection is voluntary or involuntary. Rather, this distinction has to be inferred. We have strong anecdotal evidence indicating that almost all voluntary disconnections occur on portable machines. Further, network partitions tend to last well under an hour, and simultaneous failure of all servers is rare. Therefore, we classify those disconnected sessions on portable computers lasting longer than one hour as voluntary.

4.4.1. Total CPU Usage

Figure 6 depicts total CPU consumption as a function of the duration of disconnection. Some of this CPU activity is generated by Venus in the process of cache management; on an otherwise idle machine, Venus' CPU usage increases with the number of files cached. To estimate this inherent overhead,



This graph shows the distribution of replay log sizes for all disconnected sessions on portable computers lasting one hour or longer.

Figure 7: Replay Log Lengths at End of Voluntary Disconnections

we measured the CPU consumption of an idle laptop with a typical complement of cached files. The observed utilization of 5.0% is shown by the solid line in Figure 6.

The dotted line in Figure 6 corresponds to the average observed CPU consumption, and corresponds to a utilization of 10.3%. This is sufficiently higher than the baseline amount of 5.0% to confirm that users do indeed work during voluntary disconnections — they don't just take their laptops home and leave them idle!

4.4.2. Mutation Activity

Figure 7 shows the distribution of replay log sizes for voluntary disconnected sessions. Earlier, we presented Figure 4(a), which showed the corresponding distribution for both voluntary and involuntary disconnected sessions. The average number of records in the two figures is quite different: 8.8 records while voluntarily disconnected versus 21 records in all disconnected sessions. The distributions are also quite different; the tail of Figure 7 is much shorter, indicating that user mutations span a narrower range of files during voluntary disconnections. An alternative way to interpret this data is that users restrict their mutation behavior when voluntarily disconnected.

4.4.3. Operation Mixes

Anecdotal evidence suggests that during voluntary disconnections, our users typically perform interactive tasks rather than compute-intensive tasks. We were curious to see if our data confirmed this.

In our data collection, the best indicator we have of usage patterns is the mix of VFS operations observed during a session. Figure 8 compares the observed frequency of VFS operations during connected and disconnected sessions. The two operations with significant differences, `vget` and `resolve`, are generated entirely within Venus and are independent of user activity. All other operations appear about as frequently in connected and disconnected sessions. Thus, the posited difference in user behavior is not reflected at this level. We conjecture that instrumentation at a higher level of abstraction than VFS operations will reveal the difference.

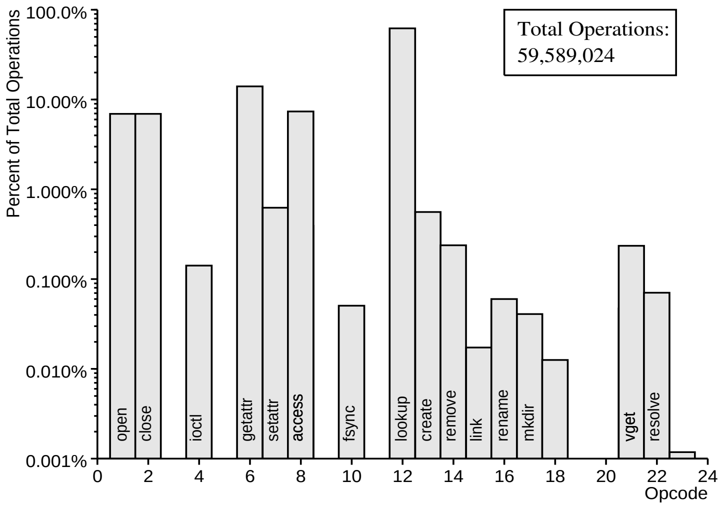
5. Conclusion

This study set out to examine the value, effectiveness and impact of the high availability aspects of Coda in day-to-day use. Our study spanned a period of 6 months, and involved serious use by a computer science research community of modest size. During this period, we found that Coda clients do experience various kinds of service failures, but that Coda is able to mask these failures effectively. Our empirical observations confirm many earlier simulation-based predictions on resource usage. They also confirm much anecdotal evidence from our user community.

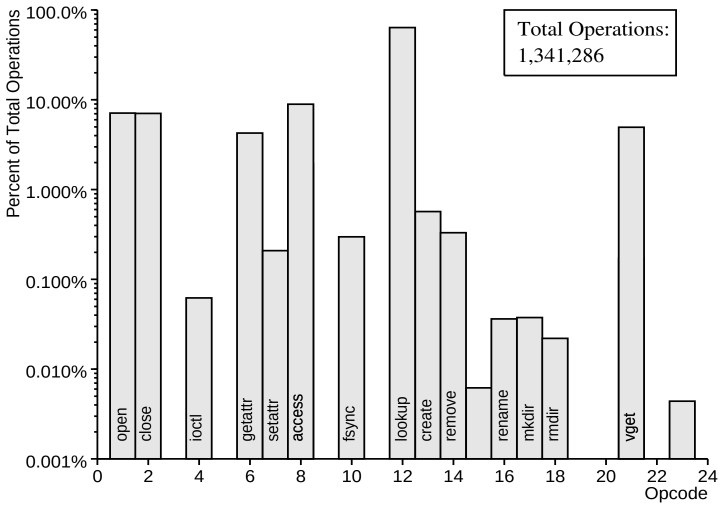
At the same time, our study has also produced some surprises and suggested avenues of further inquiry. For example, we did not anticipate the large number of transient sessions. We were also surprised by the substantial number of reintegration failures due to self-conflict. Another surprise is the tendency of users to limit mutation activity while voluntarily disconnected. A disappointing aspect of our results is their inability to corroborate the strong anecdotal evidence from users that they perform substantially different tasks when voluntarily disconnected. These suggest further evaluation of how mobility effects user behavior, and how Coda's support of mobile computing helps or hinders this behavior.

Coda is being enhanced along many different dimensions. It will soon support the ability to use low-bandwidth communication links. It will also offer improvements to resolution, reintegration, and cache management. More powerful, lighter-weight portable Coda laptops will soon be available to our user community. Finally, our user community continues to grow in size and diversity.

It is difficult to predict what the cumulative effect of these changes will be. The data collection mechanism described here is an integral part of our system, and its impact on users is negligible. We therefore plan to continue our data collection, and to periodically revisit and evolve the analysis presented in this paper.



(a) Connected Operations in Venus



(b) Disconnected Operations in Venus

This figure contrasts the operation mixes in connected and disconnected sessions. Figure 8(a) shows operations in connected sessions, and Figure 8(b) shows operations in disconnected ones. The y axis is $\log_{10}$ scaled in both figures, and any operation with a frequency below 0.001% does not appear on this graph.

The operations and corresponding opcodes in this table are: open (1), close (2), rdwr (3), ioctl (4), select (5), getattr (6), setattr (7), access (8), readlink (9), fsync (10), inactive (11), lookup (12), create (13), remove (14), link (15), rename (16), mkdir (17), rmdir (18), symlink (19), readdir (20), vget (21), resolve (22), and reintegrate (23).

Figure 8: VFS Operation Mix During Connected and Disconnected Operation

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