Reliable Data Storage in Distributed Hash Tables

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Abstract

Distributed Hash Tables offer a resilient lookup service for unstable distributed environments. Resilient data storage, however, requires additional data replication and maintenance algorithms. These algorithms can have an impact on both the performance and the scalability of the system. In this paper, we describe the goals and design space of these replication algorithms.

We examine an existing replication algorithm and present a new analysis of its reliability. We then present a new dynamic replication algorithm which can operate in unstable environments. We give several possible replica placement strategies for this algorithm, and show how they impact reliability and performance.

Finally we compare all replication algorithms through simulation, showing quantitatively the difference between their bandwidth use, fault tolerance and performance.

1 Introduction

Grid Computing and Content Distribution applications place demanding scalability and fault tolerance requirements on underlying services. Client-Server based solutions have often encountered problems meeting these requirements [1, 7].

Peer to peer technology has demonstrated excellent scalability in file sharing applications[17]. It seems likely this potential will be invaluable in solving scalability problems for more legitimate grid service applications.

Much recent research in the area of peer to peer computing has focused around various kinds of distributed hash table (DHT). These algorithms provide scalable fault tolerant key based routing. Key lookups can be routed reliably to the host responsible for them, which return any associated data.

In this paper we explore the potential of Distributed Hash Tables to provide reliable, scalable and consistent storage of mutable data. We show how the choice of replication algorithm can affect the performance, reliability and bandwidth costs of storing data in a Hash Table, a topic that has previously received little attention.

We will first give a brief overview of distributed hash tables, and describe the aims and design space of replication algorithms.

We then describe both an existing replication algorithm and a new replication algorithm based on dynamic replication[18], but adapted to provide reliability in an unstable environment, investigating the performance and reliability of both.

We then provide an analysis of the impact of various replica placement strategies possible with our dynamic replication algorithm. We show that replica placement can have a significant impact on the reliability and performance of the system.

Finally, we use a simulation to give a quantitative comparison of the performance and bandwidth costs of the algorithms we have described.

2 Distributed Hash Tables

Distributed hash tables provide a solution to the lookup problem in distributed systems. Given the name of a data item stored in the system, we can locate the node on which that data item should be stored. Most DHTs aim to find the responsible node with delay logarithmic in the number of nodes in the network.

There are many different DHT implementations, including PAST[16], Tapestry[22], CAN[14], Kademlia[9] and Chord/DHash [11]. A node in a DHT is typically responsible for the data close to it according to some distance function. Each node
maintains knowledge about a small proportion of other nodes in the network, and uses these to forward requests for keys it does not own to nodes which are closer to the requested key. Usually, the distance is reduced by a constant fraction at each routing hop, leading to lookup time logarithmic in the number of nodes.

In any large scale distributed system, nodes are likely to be joining and leaving the system constantly. These changes in the set of participating nodes are called churn. DHT routing is often tolerant of node churn, but storage is not. When a node fails, the key-value pairs it was responsible for become inaccessible, and must be recovered from elsewhere. This means that to provide reliability a replication algorithm must store and maintain backup copies of data. It must do this in a manner scalable both in the number of nodes and the quantity of data stored in the DHT.

In this paper, we will discuss replication in the context of Chord. Briefly, Chord nodes and data items are given IDs between 0 and some maximum $K$, which map to positions on a ring. The distance function between IDs is the clockwise distance around the ring between them. A node owns, or is responsible for, data that it is the first clockwise successor of. In order to route key requests, each node maintains knowledge of its immediate clockwise neighbors, called its successors, and several other nodes at fractional distances around the ring from it, called its fingers. Space concerns prohibit giving a full description of Chord, and for a full description readers are encouraged to consult the original paper[11]

## 3 The Aims of Replication

A Replication algorithm aims to achieve some combination of the following design goals.

**Reliability** The replication algorithm must not rely on any single node, and must recover from churn without user intervention.

**Scalability** The replication algorithm should scale to storing large quantities of data on a large number of nodes, $N$. So as not to limit the scalability of Chord, per node replication algorithm state and bandwidth usage should be $O(\log(N))$.

**Lookup latency** The replication algorithm may reduce the time taken to look up information by placing replicas of data in a manner that allows network locality to be exploited.

**Mutability** Updating data involves enumerating all replicas. Once this is done, a distributed commit protocol can be used to update the data consistently at all locations. For this reason, enumerating all replicas should be as fast as possible.

**Load balancing** The replication algorithm may provide caches of more popular items in order that the load is evenly balanced among all the nodes in the network.

**Consistency** If the replication algorithm is to work with mutable data, it should seek to provide clear guarantees about the consistency of replicas.

Different algorithms achieve these aims to varying extents. The choice of replication strategy may depend on which goals are more important to the task being considered.

Other aims may include resilience to malicious nodes, anonymity or privacy. These are important goals, but we consider them orthogonal to the replication problem, and best treated separately.

## 4 Replication Algorithms

A replication algorithms can be characterized by its approach to four key problems:

**Replica Maintenance** Node churn will cause replicas to be lost. The replication algorithm must detect and repair these lost replicas without using excessive bandwidth.

**Replica Addressability** In order to update an item, we need to locate all replicas of that item. Ways of doing this include limiting replica placement to a fixed number of nodes, searching for replicas, and periodically deleting old replicas.

**Replica Placement** The replica placement strategy determines which nodes replicas should be stored on. This can have an impact on both performance and reliability.
Replica Cardinality  The number of replicas we keep of a given key may either be fixed in advance, or allowed to vary according to the key’s popularity. Variable cardinality often provides superior load balancing, but makes addressability more difficult to achieve.

In this paper, we consider replication by storing a complete copy of the data associated with each key on another node. We believe that the algorithms we will describe could, with some adaptation, also be applied to erasure coded fragments of the original data, with possible performance benefits in some circumstances[15].

We will now give details of how two replication algorithms approach these tasks.

5 DHash Replication

This replication algorithm is a combination of the replica placement strategy first proposed in the original Chord paper[11], and a maintenance algorithm proposed in [4]. The techniques are combined in the DHash[3] storage system.

The placement strategy is simple, replicas of a data item are placed on the $r$ successors of the node responsible for that data item and nowhere else.

Newly joined nodes will inherit a keyspace from the node they precede, and are sent the data they become responsible for when the maintenance algorithm next runs.

The DHash maintenance algorithm runs two maintenance protocols in order to prevent the number of replicas from either dropping too low or rising too high:

Local Maintenance  A node sends a SYNCHRONIZE message containing the key range it is responsible for to its $r$ successors. These nodes then synchronize the contents of their databases so that all keys in this range are stored on both the root node and its successors.

Efficient methods for database synchronization, such as Merkle Tree hashing[10], are discussed in [4].

Global Maintenance  A node periodically checks its database of keys to see if it has any keys it is no longer responsible for. To do this, it looks up the owner of each key it stores, and checks the successor list of that owner.

If it is within $r$ hops of the node, then it will be within the first $r$ items of the successor list.

If its ID is not in this list, the node is no longer responsible for keeping a replica of this item, and the node offers the data item to the current owner. It can then safely delete the key.

If all replicas are to be repaired by a single maintenance call, the local maintenance algorithm must run two passes, the first gathering all replicas in the root nodes key range onto the root node, the second distributing these replicas onto all successors.

5.1 Fetch Algorithm

If we adopt this replication algorithm, we can use the following fetch algorithm to retrieve the data associated with a key. This algorithm will also share the load of providing a data item between all the replica holders.

| Algorithm 1 Fetch for $key$ under Successor Replication |
|---------------------------------------------------------|
| $successors ← findSuccessors(key)$                      |
| while ¬$item$ and ¬$successors.isEmpty() do             |
| $node ← successors.popRandom()$                        |
| $item ← node.get(key)$                                  |
| end while                                               |

5.2 Maintenance and Reliability

In order to keep the system reliable, we must both store replicas and repair them regularly. The more replicas we keep, the less frequently maintenance is required. This means that, for a given level of reliability, there is a trade-off between the bandwidth used by maintenance algorithm runs and the disk space used for storing replicas.

Here, we attempt to give some new insight into this trade-off, and show the level of replication and maintenance necessary to provide a given level of reliability.

For a given data item to be lost, all $r$ of the nodes holding replicas of it must fail. If a replica is missing from the system with probability $p$, the probability of a given data item being lost is simply $p^r$.  

3
For the purposes of providing reliable storage, however, we are concerned not with the probability of a given item being lost, but with the probability of data loss anywhere in the system. For this to happen, a node and its $r$ successors must all have failed at some point in the ring.

To determine this probability, we model the chord ring as a sequence of $N$ nodes, each of which is missing replicas with probability $p$. The probability of data loss in this model is equivalent to that of obtaining a sequence of $r$ successful outcomes in $N$ Bernoulli trials with probability of success $p$. This is known as the Run Problem, and the general solution, $RUN(p, r, N)$, can be given in terms of a generating function[21].

$$F(p, r, s) = \frac{p^r s^r (1 - ps)}{1 - s + (1 - p) p^r s^{r+1}} = \sum_{i=r}^{\infty} c_i p^i s^i$$

$$RUN(p, r, N) = \sum_{i=r}^{N} c_i p^i$$

In order to relate this to maintenance intervals, we need to determine the proportion of replicas missing from the ring. We will do this in terms of the number of maintenance calls in one half life, $S$. A network’s half life is the minimum of the times taken for $N/2$ of the nodes to leave, and the time $N/2$ nodes take to join. We will consider only stable state systems, where nodes join and leave the network at the same rate.

After one half-life, half of the nodes are newly joined, and contain no data$^1$, so we take $p = \frac{1}{2}$. We assume churn occurs at a constant rate, so that a fraction $\frac{1}{2}$ of the way through a half life, $p = \frac{1}{2^S}$.

We make the simplifying assumption that data transfer time is a negligible proportion of the half life, so that a maintenance call will instantly return the system to its ideal state, provided no data has been lost completely before it runs. Each half life can then be divided into $S$ independent maintenance intervals, during each of which data is lost with probability $RUN\left(\frac{1}{2^S}, r, N\right)$. The overall data loss probability is the probability that any of these

$^1$This is also a simplification. Although most missing data is caused by empty new nodes, a node also stores data on its $r$ successors, and so a failure causes one fewer replica to be stored. Taking this into account gives the fraction of missing replicas as $\frac{2r+1}{2r^2}$. Our approximation is fair for large $r$.

Figure 1: Minimum repairs necessary to maintain $FAIL(N, r, S) = 10^{-6}$ for $N = 500$

$S$ maintenance intervals loses data, and so is given by:

$$FAIL(N, r, S) = 1 - (1 - RUN\left(\frac{1}{2^S}, r, N\right))^S$$

We can use this to determine how often the maintenance algorithm needs to run in order to maintain a given failure probability. Figure 1 shows the minimum maintenance frequency necessary to maintain $FAIL(500, r, S) = 10^{-6}$, where $r$ varies from 4 to 20. We can see that there is a clear trade-off between bandwidth use and storage space. The number of maintenance calls necessary drops rapidly as we increase the number of replicas.

Figure 2 shows how network size affects the level of maintenance necessary. $N$ is varied from 50 to 500 for several values of $r$. For small $r$, the network size has a significant impact on the required maintenance frequency. As we increase $r$, network size becomes less important in determining maintenance frequency.

It should be noted that in systems where data size is large or half-life is short, so that data transfer times become a significant fraction of a half life, our assumptions are not valid and more frequent maintenance or a larger numbers of replicas will be necessary.
Figure 2: Minimum repairs necessary to maintain $FAIL(N, r, S) = 10^{-6}$ in networks of size $N = 50, 100, 200, 500$, with $r = 6, 8, 10, 12, 15$.

5.3 Maintenance and Fetch Latency

As we allow the number of replicas to drop between maintenance intervals, we increase the likelihood that we will need to contact more than one node to find the data. If we again approximate the probability of a node not having data as $\frac{1}{2S}$ then the number of nodes we need to contact, or probe, before data is found will be geometrically distributed, with expected value:

$$E(probes) = \frac{2S}{2S - 1}$$

6 Dynamic Replication

Replica Enumeration, as proposed in [18], aims to remove some of the placement and cardinality restrictions imposed by successor replication, whilst preserving addressability and the ability to make consistent updates.

The placement strategy for Replica enumeration is based around an allocation function, $h(m, d)$. For each document with ID $d$, the replicas are placed at replica locations determined by $h(m, d)$ where $m \geq 1$ is the index of that instance. The allocation function is intended to be pseudo-random, so that the replicas are evenly distributed about the address space.

The replication cardinality is variable in a fixed range $1 \leq r \leq R_{MAX}$, allowing greater replication for items in greater demand. The mechanism used to decide the exact number of replicas is not specified, but could be designed to adapt to both the reliability of the network, and the load on those nodes providing each document.

To provide addressability, the following invariants are maintained:

1. Replicas of an item $d$ are only placed at addresses given by $h(m, d)$, where $1 \leq m \leq R_{MAX}$.
2. For any document $d$ in the system, there always exists an initial replica at $h(1, d)$.
3. Any further replica with $(m > 1)$ can only exist if a replica currently exists for $m - 1$.

4. Various strategies for finding data are possible in this scheme. One that is generally efficient is to do a binary search over the range $[1..R_{MAX}]$ starting from a randomly selected index in that range. If the data is not replicated at a given location, we use invariant three to reduce the search range accordingly.

Dynamic replication can help alleviate the lookup bottleneck that affects Successor replication. Successor replication requires that all lookups for a popular key are directed to that key’s owner. With an appropriate allocation function, dynamic replication can place replicas at evenly spread, well known, locations around the ring. Lookup queries for the owner of a popular item are then distributed more evenly.

6.1 Maintenance algorithm

A major difficulty with the dynamic replication algorithm as originally provided is that maintaining these invariants in a system with a high churn rate is very difficult. Node departures and arrivals could cause any of the invariants to be violated.

It can be shown that lookups will proceed correctly as long as at least invariant two holds. However, for replica addressability, invariants one and four must also hold.

We modify the algorithm given in [18] with a maintenance algorithm to allow it to operate correctly and reliably in a system with high churn rates.

We will use the following definitions to refer to the various roles nodes play in holding replicas:
1. The node responsible for \( h(1, d) \) is the owner of \( d \).

2. The replica group for an item \( d \) are those nodes whose keyspace includes a replica location from the set \( \{ h(m, d) : 1 \leq m \leq R_{\text{MAX}} \} \).

3. The core group for an item \( d \) is the set of replica holders for which \( m \leq R_{\text{MIN}} \).

4. The peripheral group are those replica holders for which \( R_{\text{MIN}} < m \leq R_{\text{MAX}} \).

Since we can not rely on any single node being available in an unreliable environment, we must modify our invariants.

1. Replicas of an item \( d \) can only be retrieved from addresses given by \( h(m, d) \) where \( \{ 1 \leq m \leq R_{\text{MAX}} \} \).

2. For any document \( d \) in the system, there exists with high probability a replica in the core group.

3. Any peripheral replica with \( m > R_{\text{MIN}} \) can only be retrieved for a single maintenance interval if no replica currently exists for \( m - 1 \).

We can now give three maintenance protocols which maintain these invariants under churn.

**Core Maintenance** The owner of a data item calculates and looks up the nodes in the core group for the data range it is responsible for. For each core replica holder, the owner and the replica holder synchronize databases over the part of owner’s keyspace which is mapped into that replica holder’s keyspace.

Core maintenance must also deal with allocation collisions, as described in the next section.

**Peripheral Maintenance** In order to maintain Invariant 3, a node which stores a replica with index \( m > R_{\text{MIN}} \) must check that a replica of that item is also held on the replica predecessor, the owner of the location with index \( m - 1 \).

For each peripheral replica a node holds, it must obtain a summary of the items with the previous index on the replica predecessor. Bloom filters[13] can be used to reduce the cost of these exchanges.

These summaries can be used to remove orphaned peripheral replicas from the system. Orphaned peripheral replicas should not be used to answer fetch requests, but should still be stored for at least one maintenance interval, as simulation shows maintenance often replaces the missing replica.

**Global Maintenance** Each node calculates the replica group for each item it holds. Any items it is no longer a replica holder for are offered to their owner, then deleted.

We cache lookups made during maintenance to reduce bandwidth costs. Cache validity is checked at regular intervals during maintenance.

This algorithm attempts to restore the system to its ideal state each time it is run. However, between runs, the system is rarely in its ideal state. Thus we must ensure the system operates correctly where the invariants do not hold. Invariant two is sufficient to ensure lookups proceed correctly, though less efficiently, as nodes fail[18].

In order to update information, we must discover how many peripheral replicas are currently in the system. To be completely certain of consistency, we must offer all updates to all owners of peripheral replica locations.

If a lower probability of a temporary inconsistency is acceptable, we can improve performance by offering updates only until we encounter a certain number of empty peripheral replica locations since, by invariant three, it becomes increasingly unlikely that any further locations are occupied. This could dramatically improve performance if \( R_{\text{MAX}} \gg R_{\text{MIN}} \).

### 6.2 Allocation Collisions

It is important that the images of a node’s key-range under \( h(m, d) \) are owned by different nodes for each \( d \). In some cases however, the allocation function will map two replicas into the keyspace of the same node. We call this an allocation collision. Each Allocation collision reduces the number of nodes in the core replica group, reducing reliability.

The core maintenance algorithm must keep track of which nodes have been allocated replicas from which key ranges. If an allocation collision occurs,
the core maintenance algorithm must instead place the collided keyspace must in the peripheral group, effectively extending the core group. This means we must choose $R_{MAX}$ so that sufficient peripheral locations are available to recover from all allocation collisions with high probability. To do this, we must understand how nodes are distributed around the ring.

Since we have $N$ nodes uniformly distributed throughout a keyspace of size $K$, the probability of a node being at a given ID is $\frac{K}{N}$. Therefore, the number of keys between nodes is geometrically distributed with $p = \frac{K}{N}$. Using standard properties of a geometric distribution[20], we can find the mean and variance of this distribution.

$$\mu = \frac{K - N}{N} \approx \frac{K}{N} \quad (\text{since } K \gg N)$$

$$\sigma^2 = \frac{K(K - 1)}{N^2} \approx \frac{K^2}{N^2} \quad (\text{since } K \gg 1)$$

To recover from allocation collisions, the range of available replica locations should be at least this size. Thus, by the central limit theorem[19], the space occupied by $r$ nodes will be normally distributed with

$$\mu \approx \frac{rK}{N}$$

$$\sigma^2 \approx \frac{rK^2}{N^2}$$

And so, by standard properties of the normal distribution, 95% of the time, the keyspace between $r$ nodes will be less than $(r + 1.645\sqrt{r}K/N)$ keys in length. To allow $r$ replicas can be stored in 95% of cases, the range of available replica locations should be at least this size.

### 6.3 Dynamic fetch algorithm

The dynamic fetch algorithm needs to choose which indexes to lookup and in which order. In many cases, algorithm 2 will give good performance.

In situations where load balancing is not critical, shorter fetch times can be attained by searching the core replica locations before trying peripheral ones.

If maintenance is infrequent, eliminating the entire range of peripheral replicas with higher indexes if one peripheral replica is found empty may result in poor performance, and simply removing the replica known to be empty may be preferable.

### 6.4 Recursive data lookup

In order to increase performance when looking up data, we use algorithm 3 to perform recursive gets. This combines the Chord lookup and get messages, which allows any node on the lookup path of a request to return a replica of the requested data, if it holds one. This avoids further lookup hops, reducing fetch latency.

#### Algorithm 2 Dynamic Fetch for key

```
indexes ← [0...R_MAX]
item ← NULL
while ¬item do
    index ← indexes.popRandom()
    item ← recursiveGet(key, h(index, key))
    if ¬item and index > R_MIN then
        indexes.removeRange(index, R_MAX)
    end if
    if indexes=[] then
        indexes ← [0...R_MAX]
    end if
end while
```

Recursive data lookup can interfere with load balancing, since some replicas are passed queries more often than others. To prevent this, an overloaded node may choose to forward a recursive get request rather than answer using its own replica.
6.5 Allocation Functions

The choice of allocation function is critical to maintenance performance. For each item \(d\) that a node owns, it must lookup and contact every node in the core replica group in order to run the core maintenance protocol.

In order that this is scalable, we must ensure that as many of these lookups as possible can be satisfied with little network communication. This requires that the allocation function maps one node's data onto a limited number of replica holders.

We suggest that for a given \(m\), \(h(m, d)\) is a translation in \(d\). This means that the image of one node's key-range is another continuous linear range of the same size. Since Chord nodes are equally distributed throughout the key space, an image of one node's key-range is owned by \(O(1)\) other nodes.

We will now give four allocation functions and explore how they impact reliability and performance. All these functions make use of \(N\), the number of nodes in the system. This value may either be supplied by the user, or estimated at run time[2].

6.5.1 Successor Allocation

\[
h(m, d) = (d + (m \cdot \frac{K}{N})) \mod K
\]

Attempting to map replicas onto successors is efficient, as the Chord Protocol maintains a list of each nodes successors on that node, so lookups can often be performed without consulting another node.

Because replica locations with different indices are relatively close together under this allocation function, we expect some allocation collisions, which must result in the creation of peripheral replicas. Using the result from section 6.2, we recommend that \(R_{MAX} - R_{MIN}\) is at least \(1.645\sqrt{R_{MIN}}\), so that \(R_{MIN}\) distinct replicas can be stored in 95% of cases. This consideration also applied to the predecessor and block allocation functions.

6.5.2 Predecessor Allocation

\[
h(m, d) = (d - (m \cdot \frac{K}{N})) \mod K
\]

Because queries are routed around the ring clockwise towards the node responsible for them, a lookup for one node is frequently routed through one of its predecessors.

Predecessor allocation aims to exploit this fact to reduce lookup latency. When a request for a document is routed through one of the replica holders, the recursive get algorithm allows them to satisfy the request before it ever reaches the node responsible, reducing the fetch latency by one or more hops.

6.5.3 Block Allocation

\[
h(m, d) = (d - (d \mod \frac{K \cdot R_{MAX}}{N})) + (d \mod \frac{K}{N}) + (m \cdot \frac{K}{N}) \mod K
\]

This allocation function attempts to make replica groups overlap entirely with core replica groups of other nearby keyranges. As will be seen in the next section, this policy provides a lower probability of data loss than other placement functions.

It also provides most of the benefits of both successor and predecessor replication, since most nodes will have replicas placed on both successors and predecessors.

This allocation function is discontinuous in \(d\), and the maintenance algorithm must be able to deal with this when mapping ranges of keys onto other nodes.

6.5.4 Finger Allocation

\[
\delta = \log_2\left(\frac{K}{N}\right)
\]

\[
h(m, d) = (d + 2^{(m+\delta)}) \mod K
\]

This allocation function again takes advantage of the information already maintained by the chord algorithm. Chord maintains routing information about nodes at fractional distances around the ring, called fingers. Placing replicas on these finger nodes reduces the number of lookups that must be made, and distributes replicas evenly around the ring.
Because of the distance between replica locations, allocation collisions are rare, and \( R_{\text{MAX}} \) may be set more conservatively than for other allocation functions.

### 6.6 Allocation functions and Reliability

The allocation function chosen has a significant impact on reliability. Block allocation, in which core replica groups for one data range overlap entirely with core groups for nearby data ranges, produces only a very few core replica groups. Finger allocation produces core replica groups which overlap very little with other replica groups, producing a large number of distinct groups.

This large number of distinct groups leads to a higher probability that any one of them will fail. We produced a simple model of a 500 node network, in which 250 nodes are marked as failed. We produced \( 10^5 \) sample networks with this model, and used them to estimate the probability of any data loss occurring in the network with varying numbers of replicas. Figure 3 shows the probability of data loss for finger, block and successor allocation functions. Block allocation is able to achieve a more reliable system with a smaller number of replicas.

We also simulated random replica placement, where replicas were placed entirely randomly using a pseudo random number generator. The results for random placement are almost identical to those for finger placement.

In figure 4, we compare the quantity of data lost, given that a failure occurs. More data is lost with block allocation functions when a rare failure does occur than other allocation functions. In many applications however, any quantity of data loss would be considered catastrophic.

### 7 Simulation

We now attempt order to quantitatively compare the performance and bandwidth usage of these replication algorithms. Due to the difficulty of managing large numbers of physical nodes[6], we chose to test the algorithms through simulation rather than through deployment.

Our simulator is based around the SimPy[12] discrete-event simulation framework, which uses generator functions rather than full threads to achieve scalability. The simulator implements a message level model of a Chord network running each of the replication algorithms described.

#### 7.1 Simulation Parameters

In our simulation, we chose parameters that might resemble a data center built from cheap commodity components. While the simulator is capable of...
running thousands of nodes, we have limited it to two hundred in most scenarios. This was in order to keep runtime reasonable for the large number of scenarios and algorithms we wish to test, and the need to repeat simulations to estimate errors.

We simulate a steady state system in which a node fails every 24 hours, shortly after which a new node replaces it. Latency between nodes is assumed to be uniform, and bandwidth is assumed to be unlimited - messages always take the same time to deliver regardless of size.

We chose fixed parameters for the chord algorithm in all simulations, with a successor list length of 10 and finger table size of 12. Chord repair is carried out at thirty minute intervals.

We also configure the GET algorithm to search the core replica group before trying the peripheral replicas. Local and Core Maintenance algorithms run two passes at each maintenance interval.

Failures are detected by timeouts, which are set to 3 hops for round trip communications. Recursive lookup timeouts are based on network size, and are set to 15 hops in a 200 node network. A shorter timeout could have been chosen, leading to shorter average lookup times, as failed lookups are detected more quickly. Short timeouts also increase bandwidth usage, however, as long-running lookups are reissued before they complete.

The system is simulated for one complete half life, during which 50,000 sample data fetches are made for randomly chosen data items, and fetch times are logged. Bandwidth usage is also logged by type, allowing separation of maintenance messages from chord repair messages. Each simulation is repeated 4 times to obtain a good estimate of the average latencies and bandwidth usage.

8 Simulation Results

8.1 Fetch Latency

The fetch latency each maintenance algorithm can achieve depends on the network size, the frequency with which it is run, and the number of replicas in the system.

Figure 6 shows how fetch times scale with maintenance frequency. The Finger and DHash algorithms both scale as predicted in section 5.3.

Maintenance frequency has less effect on Successor, Predecessor and Block fetch times. The proximity of different replica indexes means that other replica holders often preemptively return data, so that it is less important that specified replica is present.

The predecessor algorithm achieves the shortest fetch times. With predecessor allocation, queries for core replicas are more often routed through peripheral replicas, which return the data preemptively. DHash fetches are never returned preemp-
tively, and are routed through the requesting node, so that they take at least one hop longer than dynamic allocation.

Figure 5 shows how fetch times scale with network size. All algorithms show logarithmic behavior, though finger allocation compares increasingly badly to other dynamic algorithms since as networks size grows, the probability of a preemptive return drops.

Increasing the number of replicas reduces the lookup times slightly, whereas increasing the number of distinct data items in the system has no impact on lookup times.

8.2 Maintenance Bandwidth Costs

Figure 7: Overhead bandwidth in a 200 Node system with varying numbers of repairs

Maintenance bandwidth can be divided into two separate costs: The cost of identifying which data should be stored where, and the cost of moving the data to that location. We refer to the former as the maintenance overhead.

In figure 7 we can see how overhead varies with maintenance frequency. DHash maintenance has lower overhead than the dynamic algorithms. Dynamic maintenance typically involves $O(r)$ lookups, where DHash requires $O(1)$. The dynamic algorithms all have similar overhead, which increases linearly with maintenance frequency. Notably, all algorithms overhead bandwidth is so small as to be negligible in most network environments.

Data movement bandwidth is likely to be the bottleneck in distributed storage systems. Figure 8 shows all dynamic algorithms move very similar quantities of data. At high maintenance levels, significantly more data is moved with DHash than the dynamic algorithms, since a single node joining produces changes in the membership of $r$ nearby replica groups, with one node leaving each group. This causes the node expelled from each of these replica groups to send any replicas it no longer owns to their owner.

Figure 9 shows the linear relationship between the number of key value pairs and maintenance overhead. Again, maintenance overhead is low for all algorithms, so that it should be feasible to store a very large numbers of items per node without maintenance bandwidth becoming a bottleneck.

Per node maintenance overhead bandwidth and total data movement remain constant as we vary the number of nodes in the system, for all algorithms. This means all algorithms will scale well to very large numbers of nodes.

8.3 Fault Tolerance

We have so far investigated the performance of these data replication algorithms under a steady state of churn, in which new nodes join at the same rate as other nodes fail. The DHT can also recover from far higher failure rates, although there is a substantial performance impact.

We simulate a simultaneous failure of a varying
proportion of the nodes in the chord network, and then launch 50,000 data fetches immediately afterward. Unlimited retries are allowed, and the average fetch time, including retries is shown in Figure 10.

The DHash algorithm is particularly affected in this scenario, due to its reliance on reaching a single node. The dynamic algorithms are more resilient to faulty routing, as they may select multiple indexes to look up, and because preemptive returns are possible even when the specific node requested is unreachable.

9 Related Work

Metadata based algorithms, such as the Version ID system used by OceanStore[8] are another possible replica management option. These algorithms do not have placement restrictions, but instead use a metadata item to locate replicas. These solutions may perform well in many scenarios, but require an underlying reliable storage system for metadata. The algorithms we have described could be used to provide such a storage system.

Soft-state storage is another common replica management system. With soft-state storage, no attempt is made to maintain replicas. Instead, data expires after some timeout and the system relies on data periodically being refreshed and reinserted by some external system. Though this can be useful for frequently refreshed data, failure of the external storage system can cause unwanted data loss.

10 Conclusions

We have used a combination of analysis and simulation to assess the ability of various replication algorithms to meet the goals we set out in section 3.

We can see that dynamic replication can achieve faster lookups, greater reliability and may require less replica movement than the DHash algorithm, with only a slightly higher maintenance overhead. We have also shown how the allocation function choice can have a dramatic impact on performance. Of the allocation functions we considered, block allocation provides the best reliability and represents a good compromise for most systems, though predecessor placement might be preferable if performance is critical.

Possible drawbacks of dynamic replication are its slightly higher maintenance bandwidth usage and its reliance on an even distribution of node IDs, which may make it unsuitable for small Chord Rings.

System size scalability is good for all maintenance algorithms. Lookup times scale with the logarithm of network size and total system bandwidth consumption scales linearly with the number
of nodes.

On an internet wide scale, bandwidth and uptime are likely to be more limited than in the data center scenarios we have considered. In such a system, the number of nodes is likely to vary throughout the day rather than remain constant. Although our work may provide insight into performance in such scenarios, further work needs to be done to assess the reliability of a system which incorporates user desktop systems.

References

[1] Augustin et al. HEP applications evaluation of the EDG testbed and middleware. http://arxiv.org/abs/cs.DC/0306027, 2003.

[2] Andreas Binzenhöfer, Dirk Staehle, and Robert Henjes. Estimating the size of a chord ring. Technical Report 348, University of Würzburg, 11 2004.

[3] Emma Brunskill. Building peer-to-peer systems with chord, a distributed lookup service. In HOTOS '01: Proceedings of the Eighth Workshop on Hot Topics in Operating Systems, page 81, Washington, DC, USA, 2001. IEEE Computer Society.

[4] Josh Cates. Robust and efficient data management for a distributed hash table. Master's thesis, Massachusetts Institute of Technology, May 2003.

[5] Frank Dabek, M. Frans Kaashoek, David Karger, Robert Morris, and Ion Stoica. Wide-area cooperative storage with CPS. In Proceedings of the 18th ACM Symposium on Operating Systems Principles (SOSP '01), Chateau Lake Louise, Banff, Canada, October 2001.

[6] David Patterson David Oppenheimer, Jeannie Albrecht and Amin Vahdat. Distributed resource discovery on planetlab with sword. In Proceedings of the First Workshop on Real, Large Distributed Systems (WORLDS '04), dec 2004.

[7] P. Clarke J. Coles D. Colling A. Doyle S.M. Fisher A.C. Irving J. Jensen A. McNab D. Britton and D. Newbold. A grid for particle physics - from testbed to production. In Proceedings of the UK e-Science All Hands Meeting, 2004.

[8] J. Kubiatowicz, D. Bindel, Y. Chen, S. Czerwinski, P. Eaton, D. Geels, R. Gummad, S. Rhea, H. Weatherspoon, W. Weimer, C. Wells, and B. Zhao. Oceandstore: an architecture for global-scale persistent storage. In Proceedings of the Ninth international Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS 2000), pages 190-201. ACM Press, November 2000.

[9] P. Maymounkov and D. Mazieres. Kademia: A peer-to-peer information system based on the xor metric. In Proceedings of IPTPS02, 2002.

[10] Ralph C. Merkle. Protocols for Public Key Cryptosystems. In Proceedings of the 1980 Symposium on Security and Privacy, pages 122–133, Oakland, CA, U.S.A., April 1980. IEEE Computer Society.

[11] Robert Morris, David Karger, Frans Kaashoek, and Hari Balakrishnan. Chord: A Scalable Peer-to-Peer Lookup Service for Internet Applications. In ACM SIGCOMM 2001, San Diego, CA, September 2001.

[12] Klaus Muller. Advanced systems simulation capabilities in simpy. In EuroPython 2004.

[13] G. L. Peterson. Time-space trade-offs for asynchronous parallel models (reducibilities and equivalences). In STOC '79: Proceedings of the eleventh annual ACM symposium on Theory of computing, pages 224–230, New York, NY, USA, 1979. ACM Press.

[14] Sylvia Ratnasamy, Paul Francis, Mark Handley, Richard Karp, and Scott Shenker. A scalable content addressable network. Technical Report TR-00-010, Berkeley, CA, 2000.

[15] Barbara Liskov (MIT) Rodrigo Rodrigues (MIT). High availability in dhts: Erasure coding vs. replication. In Proceedings of IPTPS05, feb 2005.

[16] Antony Rowstron and Peter Druschel. Storage management and caching in past, a large-scale, persistent peer-to-peer storage utility. In Proceedings of the 18th SOSP (SOSP '01), Chateau Lake Louise, Banff, Canada, October 2001.

[17] S. Saroiu, P. Gummadi, and S. Gribble. A measurement study of peer-to-peer file sharing systems, 2002.

[18] Marcel Waldvogel, Paul Hurley, and Daniel Bauer. Dynamic replica management in distributed hash tables. Research Report RZ-3502, IBM, July 2003.

[19] Eric W. Weisstein. Central limit theorem. From MathWorld–A Wolfram Web Resource.

[20] Eric W. Weisstein. Geometric distribution. From MathWorld–A Wolfram Web Resource.

[21] Eric W. Weisstein. Run. From mathworld–a wolfram web resource.

[22] Ben Y. Zhao, Ling Huang, Jeremy Stribling, Sean C. Rhea, Anthony D. Joseph, and John D.
Kubiatowicz. Tapestry: A resilient global-scale overlay for service deployment. *IEEE Journal on Selected Areas in Communications*, 22(1):41–53, Jan 2004.