Glacier: Highly durable, decentralized storage despite massive correlated failures

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Abstract

Decentralized storage systems aggregate the available disk space of participating computers to provide a large storage facility. These systems rely on data redundancy to ensure durable storage despite of node failures. However, existing systems either assume independent node failures, or they rely on introspection *to carefully place redundant data on nodes with low expected failure correlation. Unfortunately, node failures are not independent in practice and constructing an accurate failure model is difficult in large-scale systems. At the same time, malicious worms that propagate through the Internet pose a real threat of large-scale correlated failures. Such rare but potentially catastrophic failures must be considered when attempting to provide highly durable storage.*

In this paper, we describe Glacier, a distributed storage system that relies on massive redundancy to mask the effect of large-scale correlated failures. Glacier is designed to aggressively minimize the cost of this redundancy in space and time: Erasure coding and garbage collection reduces the storage cost; aggregation of small objects and a loosely coupled maintenance protocol for redundant fragments minimizes the messaging cost. In one configuration, for instance, our system can provide six-nines durable storage despite correlated failures of up to 60% of the storage nodes, at the cost of an elevenfold storage overhead and an average messaging overhead of only 4 messages per node and minute during normal operation. Glacier is used as the storage layer for an experimental serverless email system.

1 Introduction

Distributed, cooperative storage systems like FarSite and OceanStore aggregate the often underutilized disk space and network bandwidth of existing desktop computers, thereby harnessing a potentially huge and self-scaling storage resource [1, 27]. Distributed storage is also a fundamental component of many other recent decentralized systems, for instance, cooperative backup, serverless messaging or distributed hash tables [15, 17, 20, 28, 31].

Since individual desktop computers are not sufficiently dependable, redundant storage is typically used in these systems to enhance data availability. For instance, if nodes are assumed to fail independently with probability p, a system of k replicas fails with probability $p^k \ll p$; the parameter k can be adjusted to achieve the desired level of availability. Unfortunately, the assumption of failure independence is not realistic [3, 4, 25, 41, 43]. In practice, nodes may be located in the same building, share the same network link, or be connected to the same power grid.

Most importantly, many of the nodes may run the same software. Results of our own recent survey of 199 random Gnutella nodes, which is consistent with other statistics [34], showed that 39% of the nodes were using the Morpheus client; more than 80% were running the Windows operating system. A failure or security vulnerability associated with a widely shared software component can affect a majority of nodes within a short period of time. Worse, worms that propagate via email, for instance, can even infect computers within a firewalled corporate intranet.

On the other hand, stored data represents an important asset and has considerable monetary value in many environments. Loss or corruption of business data, personal records, calendars or even user email could have catastrophic effects. Therefore, it is essential that a storage system for such data be sufficiently dependable. One aspect of dependability is the *durability* of a data object, which we define, for the purposes of this paper, as the probability that a specific data object will survive an assumed worst-case system failure.

Large-scale correlated failures can be observed in the Internet, where thousands of nodes are regularly affected by virus or worm attacks. Both the frequency and the severity of these attacks have increased dramatically in recent years [39]. So far, these attacks have rarely caused data losses. However, since the malicious code can often obtain administrator privileges on infected machines, the attackers could easily have erased the locals disks had they intended to do serious harm.

In this paper, we describe Glacier, a distributed storage system that is robust to large-scale correlated failures. Glacier's goal is to provide highly durable, decentralized storage suitable for important and otherwise unrecoverable data, despite the potential for correlated, Byzantine failures of a majority of the participating storage nodes. Our approach is 'extreme' in the sense that, in contrast to other approaches [23, 27], we assume the exact nature of the correlation to be unpredictable. Hence, Glacier must use redundancy to prepare for a wide range of failure scenarios. In essence, Glacier trades efficiency in storage utilization for durability, thus turning abundance into reliability.

Since Glacier does not make any assumptions about the nature and correlation of faults, it can provide hard, analytical durability guarantees. The system can be configured to prevent data loss even under extreme conditions, such as correlated failures with data loss on 85% of the storage nodes or more. Glacier makes use of erasure codes to spread data widely among the participating storage nodes, thus generating a degree of redundancy that is sufficient to survive failures of this magnitude. Aggregation of small objects and a loosely coupled fragment maintenance protocol reduce the message overhead for maintaining this massive redundancy, while the use of erasure codes and garbage collection of obsolete data mitigate the storage cost.

Despite these measures, there is a substantial storage cost for providing strong durability in such a hostile environment. For instance, to ensure an object survives a correlated failure of 60% of the nodes with a probability of .999999, the storage overhead is about 11-fold. Fortunately, disk space on desktop PCs is a vastly underutilized resource. A recent study showed that on average, as much as 90% of the local disk space is unused [9]. At the same time, disk capacities continue to follow Moore's law [22]. Glacier leverages this abundant but unreliable storage space to provide durable storage for critical data. To the best of our knowledge, Glacier is the first system to provide hard durability guarantees in such a hostile environment.

The rest of this paper is structured as follows: In the next section, we give an overview of existing solutions for ensuring long-term data durability. Section 3 describes the assumptions we made in the design of our system, and the environment it is intended for. In the following two sections, we demonstrate how Glacier can lend a distributed hash table data durability in the face of large-scale correlated failures. We discuss security aspects in Section 6 and describe our experimental evaluation results in Section 7. Finally, Section 8 presents our conclusions.

2 Related work

OceanStore [27] and Phoenix [23, 24] apply *introspection* to defend against the threat of correlated failures. OceanStore relies primarily on inferring correlation by observing actual failures, whereas Phoenix proactively infers possible correlations by looking at the configuration of the system, e.g. their operating system and installed software. In both systems, the information is then used to place replicas of an object on nodes that are expected to fail with low correlation.

However, the failure model can only make accurate predictions if it reflects *all* possible causes of correlated failures. One possible conclusion is that one has to carefully build a very detailed failure model. However, a fundamental limitation of the introspective approach is that observation does not reveal low-incidence failures and it is difficult for humans to predict all sources of correlated failures. For instance, a security vulnerability that exists in two different operating systems due to a historically shared codebase is neither observable, nor are developers or administrators likely to be aware of it prior to its first exploit.

Moreover, introspection itself can make the system vulnerable to a variety of attacks. Selfish node operators may have an incentive to provide incorrect information about their nodes. For example, a user may want to make her node appear less reliable to reduce her share of the storage load, while an attacker may want to do the opposite in an attempt to attract replicas of an object he wants to censor. Finally, making failure-related information available to peers may be of considerable benefit to an attacker, who may use it to choose promising targets.

Introspective systems can achieve robustness to correlated failures at a relatively modest storage overhead, but they assume an accurate failure model, which involves risks that are hard to quantify. Glacier is designed to provide very high data durability for important data. Thus, it chooses a point in the design space that relies on minimal assumptions about the nature of failures, at the expense of larger storage overhead compared to introspective systems.

TotalRecall [5] is an example of a system that uses introspection to optimize availability under churn. Since this system does not give any worst-case guarantees, our criticism of introspection does not apply to it.

OceanStore [27], like Glacier, uses separate mechanisms to maintain short-term availability and to ensure long-term durability. Unlike Glacier, OceanStore cannot sustain Byzantine failures of a large fraction of storage nodes [44].

Many systems use redundancy to guard against data loss. PAST [20] and Farsite [1] replicate objects across multiple nodes, while Intermemory [14], Free-

Haven [18], Myriad [13], PASIS [45] and other systems [2] use erasure codes to reduce the storage overhead for the redundant data. Weatherspoon et al. [42] show that erasure codes can achieve mean time to failures many orders of magnitude higher than replicated systems with similar storage and bandwidth requirements. However, these systems assume only small-scale correlated failures or failure independence. Systems with support for remote writes typically rely on quorum techniques or Byzantine fault tolerance to serialize writes and thus cannot sustain a catastrophic failure.

Cates [12] describes a data management scheme for distributed hashtables that keeps a small number of erasure-coded fragments for each object to decrease fetch latency and to improve robustness against small-scale fail-stop failures. The system is not designed to sustain large-scale correlated failures or Byzantine faults.

Glacier spends a high amount of resources to provide strong worst-case durability guarantees. However, not all systems require this level of protection; in some cases, it may be more cost-effective to optimize for expected failure patterns. Keeton et al. [26] present a quantitative discussion of the tradeoff between cost and dependability.

Glacier uses leases to control the lifetime of stored objects, which need to be periodically renewed to keep an object alive. Leases are a common technique in distributed storage systems; for example, they have been used in Tapestry [46] and CFS [17].

A particularly common example of correlated failures are Internet worm attacks. The course, scope and impact of these attacks has been studied in great detail [29, 30, 38, 39, 47].

3 Assumptions and intended environment

In this section, we describe assumptions that underlie the design of Glacier and the environment it is intended for.

Glacier is a decentralized storage layer providing data durability in the event of large-scale, correlated and Byzantine storage node failures. It is intended to be used in combination with a conventional, decentralized replicating storage layer that handles normal read and write access to the data. This *primary storage* layer might typically keep a small number of replicas of each data object, sufficient to mask individual node failures without loss in performance or short-term availability.

Glacier is primarily intended for an environment consisting of desktop computers within an organizational intranet, though some fraction of nodes are assumed to be notebooks connected via a wireless LAN or home desktops connected via cable modems or DSL. Consistent with this environment, we assume modest amounts of churn and relatively good network connectivity. A substantial fraction of the nodes is assumed to be online most of the time, while the remaining nodes (notebooks and home desktops) may be disconnected for extended periods of time. In the following, we outline key assumptions underlying Glacier's design.

3.1 Lifetime versus session time

We define the *lifetime* of a node as the time from the instant when it first joins the system until it either permanently departs or it loses its locally stored data. The *session time* of a node is the time during which it remains connected to the overlay network. We assume that the expected lifetime of a node is high, at least on the order of several weeks. Without a reasonably long lifetime a cooperative, persistent storage system is infeasible since the bandwidth overhead of moving data between nodes would be prohibitive [6]. Glacier is intended for an environment similar to the one described by Bolosky et al. [8], where an expected lifetime of 290 days was reported.

However, session times can be much shorter, on the order of hours or days. Nodes may go offline and return with their disk contents intact, as would be expected of notebooks, home desktops, or desktops that are turned off at night or during weekends.

3.2 Failure model

We assume that Glacier is in one of three operating modes at any given time: *normal*, *failure* or *recovery*. During *normal operation*, only a small fraction of nodes is assumed to be faulty at any time, though a strong minority of the nodes may be off-line. In this mode, Glacier performs the background tasks of aggregation, coding and storage of newly written data, garbage collection, and fragment maintenance.

During a *large-scale failure*, a majority of the storage nodes, but not more than a fraction f_{max}, have suffered Byzantine failures virtually simultaneously. In this mode, we cannot assume that communication within the system is possible, and Glacier's role is limited to protecting the data stored on non-faulty nodes. It is sufficient to choose f_{max} as a loose upper bound, which can be estimated from the overall amount of diversity in the system. The failure state is assumed to last less than Glacier's *object lease period* L_O.

Glacier enters *recovery mode* when sysadmins have recovered or taken off-line enough of the faulty nodes so that communication within the system is once again possible. In this mode, Glacier reconstitutes aggregates from surviving fragments and restores missing fragments. Note that Glacier does not explicitly differentiate between the three modes.

3.3 Requirements

Glacier assumes that the participating storage nodes form an overlay network. The overlay is expected to provide a distributed directory service that maps numeric keys to the address of a live node that is currently responsible for the key. Glacier assumes that the set of possible keys forms a circular space, where each live participating node is responsible for an approximately uniformly sized segment of the key space. This segment consists of all keys closest to the node's identifier. Participating nodes store objects with keys in their segment. If a node fails, the objects in its local store may be lost.

To prevent Sybil attacks [19], node identifiers are assigned pseudo-randomly and it is assumed that an attacker cannot acquire arbitrarily many legitimate node identifiers. This can be ensured though the use of *certified node identifiers* [10].

Structured overlay networks with a distributed hash table (DHT) layer like DHash/Chord [16, 40] or PAST/Pastry [20, 37] provide such a service, though other implementations are possible. Glacier requires that it can always reliably identify, authenticate and communicate with the node that is currently responsible for a given key. If the overlay provides secure routing techniques, such as those described by Castro et al. [10], then Glacier can tolerate Byzantine failures during normal operation.

Glacier assumes that the participating nodes have loosely synchronized clocks, for instance by running NTP [33]. Glacier does not depend on the correctness of its time source, nor the correctness of the overlay directory services during large-scale failures.

4 Glacier

The architecture of Glacier is depicted in Figure 1. Glacier operates alongside a *primary store*, which maintains a small number of full replicas of each data object (e.g., 2–3 replicas). The primary store ensures efficient read and write access and provides short-term availability of data by masking individual node failures. Glacier acts as an archival storage layer, ensuring long-term durability of data despite large-scale failure. The aggregation layer, described in Section 5, aggregates small objects prior to their insertion into Glacier for efficiency. Objects of sufficient size can be inserted directly into Glacier.

During normal operation, newly written or updated data objects are aggregated asynchronously. Once a sufficiently large aggregate has accumulated or a time limit is reached, Glacier erasure codes the aggregate and places the fragments at pseudo-randomly selected storage nodes throughout the system. Periodically, Glacier

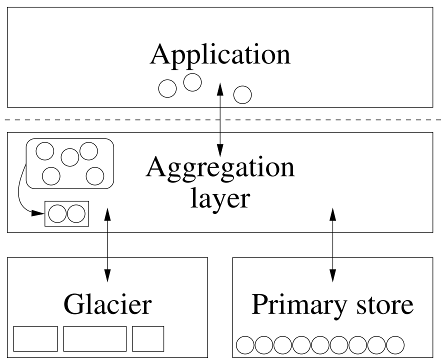


Figure 1. Structure of a multi-tier system with Glacier and an additional aggregation layer.

consolidates remaining live objects into new aggregates, inserts the new fragments and discards fragments corresponding to old aggregates.

Once an object is stored as part of an erasure coded aggregate, Glacier ensures that the object can be recovered even if the system suffers from a large-scale, correlated Byzantine failure. The *durability guarantee* given by Glacier implies that, if the failure affects a fraction $f \leq f_{max}$ of the storage nodes, each object survives with probability $P \geq P_{min}$. The parameters f_{max} and P_{min} determine the overhead and can be adjusted to the requirements of the application.

Glacier ensures durability by spreading redundant data for each object over a large number of storage nodes. These nodes periodically communicate with each other to detect data loss, and to re-create redundancy when necessary. After a large-scale failure event, Glacier reconstitutes aggregates from surviving fragments and reinserts objects into the primary store. The recovery proceeds gradually to prevent network overload. Additionally, an on-demand primitive is available to recover objects synchronously when requested by the application.

4.1 Interface to applications

Glacier is designed to protect data against Byzantine failures, including a failures of the node that inserted an object. Therefore, there are no primitives to either delete or overwrite existing data remotely. However, *leases* are used to limit the time for which an object is stored; when its lease expires, the object can be removed and its storage is reclaimed. Application must renew the leases of all objects they care about once per lease period. The lease period is chosen to exceed the assumed maximal duration of a large-scale failure event, typically several weeks or months. Also, since objects in Glacier are effectively immutable, updated objects must be inserted with a different *version number*.

Applications interact with Glacier by invoking one of the following methods:

- `put(i,v,o,l)` stores an object o under identifier i and version number v, with a lease period of l.
- `get(i,v)`$\rightarrow$`o` retrieves the object stored under identifier i and version number v. If the object is not found, or if its lease has expired, `nil` is returned.
- `refresh(i,v,l)` extends the lease of an existing object. If the current lease period of the object already exceeds l, the operation has no effect.

4.2 Fragments and manifests

Glacier uses an *erasure code* [35] to reduce storage overhead. We use a variant of Reed-Solomon codes based on Cauchy matrices [7], for which efficient codecs exist. However, any other erasure code could be used as well. An object O of size $|O|$ is recoded into n *fragments* $F_1, F_2, \ldots, F_n$ of size $\frac{|O|}{r}$, any r of which contain sufficient information to restore the entire object. If possible, each fragment is stored on a different node, or *fragment holder*, to reduce failure correlation among fragments.

If the object O is stored under a key k, then its fragments are stored under a *fragment key* (k, i, v), where i is the index of the fragment and v is a version number. For each version, Glacier maintains an independent set of fragments. If an application creates new versions frequently, it can choose to bypass Glacier for some versions and apply the corresponding modifications to the primary storage system only.

For each object O, Glacier also maintains an *authenticator*

$$A_O = (H(O), H(F_1), H(F_2), \ldots, H(F_n), v, l)$$

where $H(f)$ denotes a secure hash (e.g., SHA-1) of f. This is necessary to detect and remove corrupted fragments during recovery, since any modification to a fragment would cause the object to be reconstructed incorrectly. The value l represents the lease associated with the object; for permanent objects, the value $l = \infty$ is used.

The authenticator is part of a *manifest* M_O, which accompanies the object and each of its fragments. The manifest may contain a cryptographic signature that authenticates the object and each of its fragments; it can also be used to store metadata such as credentials or billing information. For immutable objects that do not require a specific, chosen key value, it is sufficient to choose $M_O = A_O$ and $k = H(A_O)$; this makes the object and each of its fragments self-certifying.

4.3 Key ownership

In structured overlays like Pastry or Chord, keys are assigned to nodes using consistent hashing. For instance, in Pastry, a key is mapped to the live node with the numerically closest node identifier. In the event of a node departure, keys are immediately reassigned to neighboring nodes in the id space to ensure availability.

In Glacier, this is both unnecessary and undesirable because fragments stored on nodes that are temporarily off-line do not need to be available and therefore do not need to be reassigned. For this reason, Glacier uses a modified assignment of keys to nodes, where keys are assigned by consistent hashing over the set of nodes that are either on-line or were last online within a period T_{max}.

4.4 Fragment placement

In order to determine which node should store a particular fragment (k, i, v), Glacier uses a *placement function* P. This function should have the following properties:

1. Fragments of the same object should be placed on different, pseudo-randomly chosen nodes to reduce inter-fragment failure correlation.
2. It must be possible to locate the fragments after a failure, even if all information except the object's key is lost.
3. Fragments of objects with similar keys should be grouped together so as to allow the aggregation of maintenance traffic.
4. The placement function should be *stable*, i.e. the node on which a fragment is placed should change rarely.

A natural solution would be to use a 'neighbor set', i.e. to map (k, i, v) to the ith closest node relative to k. Unfortunately, this solution is not stable because the arrival of a new node in the vicinity of k would change the placement of most fragments. Also, choosing $P(k, i, v)$ as the content hash of the corresponding fragment is not a solution because it does not allow fragments to be located after a crash. Instead, Glacier uses

$$P(k, i, v) = k + \frac{i}{n+1} + H(v)$$

This function maps the primary replica at position k and its n fragments to $n + 1$ equidistant points in the circular id space (Figure 2). If multiple versions exist, the hash $H(v)$ prevents a load imbalance by placing their fragments on different nodes.

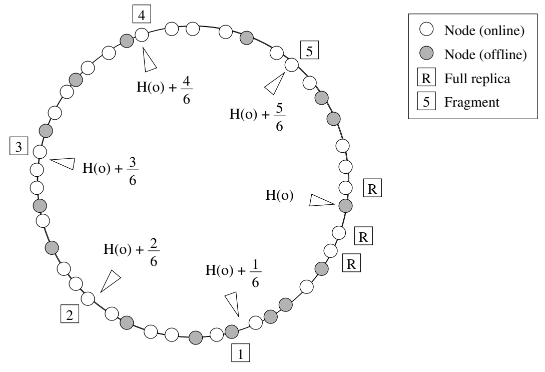


Figure 2. Fragment placement in a configuration with five fragments and three replicas in the primary store.

When a new object (k, v) must be inserted, Glacier uses the overlay to send probe messages to each location $P(k, i, v), i = 1..N$. If the owner of $P(k, i, v)$ is currently online, it responds to this message, and Glacier sends the fragment directly to that node. Otherwise, the fragment is discarded and restored later by the maintenance mechanism.

If the availability of the nodes is very low, there may be situations where fewer than r fragment holders are online during insertion. In this case, the inserting node sends additional probe messages, which are answered by one of the owners' neighbors. These neighbors then act as temporary fragment holders. When an owner rejoins the overlay, its neighbors learn about it using the standard overlay mechanisms and then deliver their fragments to the final destination.

4.5 Fragment maintenance

Ideally, all N fragments of each object would be available in the network and stored on their respective fragment holders. However, there are various reasons why real Glacier installations may deviate from this ideal state: Nodes may miss fragment insertions due to short-term churn, key space ownership may change due to node joins and departures, and failures may cause some or all fragments stored on a particular node to be lost. To compensate for these effects, and to avoid a slow deterioration of redundancy, Glacier includes a *maintenance* mechanism.

Fragment maintenance relies on the fact that the placement function assigns fragments with similar keys to a similar set of nodes. If we assume for a moment that the nodeId distribution is perfectly uniform, each fragment holder has $N-1$ peers which are storing fragments of the exact same set of objects as itself. Then, the following simple protocol can be used:

1. The node compiles a list of all the keys (k, v) in its local fragment store, and sends this list to some of its peers.
2. Each peer checks this list against its own fragment store and replies with a list of manifests, one for each object missing from the list.
3. For each object, the node requests k fragments from its peers, validates each of the fragments against the manifest, and then computes the fragment that is to be stored locally.

With realistic nodeId distributions, the local portion of key space may not perfectly match that of the peer, so the node may have to divide up the list among multiple nodes. In very small networks, the placement function may even map more than one fragment to a single node, which must be accounted for during maintenance.

Glacier uses Bloom filters as a compact representation for the lists. To save space, these filters are parametrized such that they have a fairly high collision rate of about 25%, which means that about one out of four keys will not be detected as missing. However, the hash functions in the Bloom filter are changed after every maintenance cycle. Since maintenance is done periodically (typically once per hour), collisions cannot persist, and every fragment is eventually recovered.

4.6 Recovery

Glacier's maintenance process works whenever overlay communication is possible. Thus, the same mechanism covers normal maintenance and recovery after a large-scale failure. Compromised nodes either fail permanently, in which case other nodes take over their key segments, or they are eventually repaired and re-join the system with an empty fragment store. In both cases, the maintenance mechanism eventually restores full redundancy. Hence, there is no need for Glacier to explicitly detect that a correlated failure has occurred.

However, care must be taken to prevent congestive collapse during recovery. For this reason, Glacier limits the number of simultaneous fragment reconstructions to a fixed number R_{max}. Since the load spreads probabilistically over the entire network, the number of requests at any particular node is also on the order of R_{max}. Since Glacier relies on TCP for communication, this approach has the additional advantage of being self-clocking, i.e. the load is automatically reduced when the network is congested.

4.7 Garbage collection

When the lease associated with an object expires, Glacier is no longer responsible for maintaining its fragments and may reclaim the corresponding storage. Since the lease is part of the authenticator, which accompanies every fragment, this process can be carried out independently by each storage node.

However, assuming closely synchronized clocks among the storage nodes would be unrealistic. Therefore, fragments are not deleted immediately; instead, they are kept for an additional *grace period* T_G, which is set to exceed the assumed maximal difference among the clocks. During this time, the fragments are still available for queries, but they are no longer advertised to other nodes during maintenance. Thus, nodes that have already deleted their fragments do not attempt to recover them.

Glacier has explicit protection against attacks on its time source, such as NTP. This feature is discussed in Section 6.

4.8 Configuration

Glacier's storage overhead is determined by the overhead for the erasure code, which is $\frac{N}{r}$, while the message overhead is determined by the number of fragments N that have to be maintained per object. Both depend on the guaranteed durability P_{min} and the maximal correlated failure fraction f_{max}, which are configurable.

Since suitable values for N and r have to be chosen *a priori*, i.e. before the failure has occurred, we do not know which of the nodes are going to be affected. Hence, all we can assume is that the unknown failure will affect any particular node with probability f_{max}. Note that this differs from the commonly assumed Byzantine failure model, where the attacker gets to choose the nodes that will fail. In our failure model, the attacker can only compromise nodes that share a common vulnerability, and these are distributed randomly in the identifier space because of the pseudo-random assignment of node identifiers.

Consider an object O whose N fragments are stored on N different nodes. The effect of the unknown correlated failure on O can be approximated by N Bernoulli trials; the object can be reconstructed if at least r trials have a positive outcome, i.e. with probability

$$D = P(s \geq r) = \sum_{k=r}^{N} \binom{N}{k} (1 - f_{max})^k \cdot f_{max}{}^{N-k}$$

The parameters N and r should be chosen such that P meets the desired level of durability. Figure 3 shows the lower bound on N and the storage overhead for different assumed values of f_{max} and for different choices of r. Table 1 shows a few example configurations.

While D represents the durability for an individual object, the user is probably more concerned about the durability of his entire collection of objects. If we as-

Failure f_{max}	Durability D	Code r	Fragments N	Storage S
0.30	0.9999	3	13	4.33
0.50	0.99999	4	29	7.25
0.60	0.999999	5	48	9.60
0.70	0.999999	5	68	13.60
0.85	0.999999	5	149	29.80
0.63	0.999999	1	30	30.00

Table 1. Example configurations for Glacier. For comparison, a configuration with simple replication (r=1) is included.

sume that the number of storages nodes is large and that keys are assigned randomly (as is the case for content-hash keys), object failures are independent, and the probability that a collection of n objects survives the failure unscathed is $P_D(n) = D^n$. Figure 4 shows a graph of P_D for different values of D.

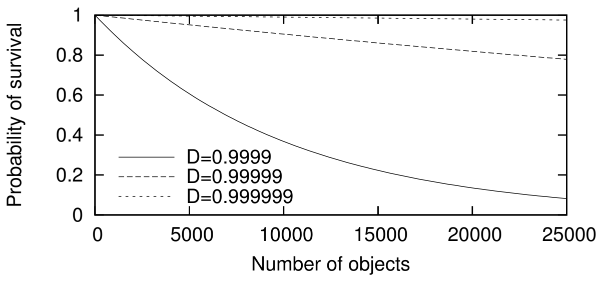


Figure 4. Probability of survival for collections of multiple objects.

If the value for f_{max} is accidentally chosen too low, Glacier still offers protection; the survival probability degrades gracefully as the magnitude of the actual failure increases. For example, if $f_{max} = 0.6$ and $P_{min} = 0.999999$ were chosen, P is still 0.9997 in a failure with $f = 0.7$, and 0.975 for $f = 0.8$. This is different in an introspective system, where an incorrect failure model can easily lead to a catastrophic data loss.

Another important parameter to consider is the lease time. If leases are short, then storage utilization is higher, since obsolete objects are removed more quickly; on the other hand, objects have to be refreshed more often. Clearly, the lease time must exceed both the maximal duration of a large-scale failure and the maximal absence of a user's node from the system. In practice, we recommend leases on the order of months. With shorter leases, users leaving for a long vacation might accidentally lose some of their data if they keep their machine offline during the entire time.

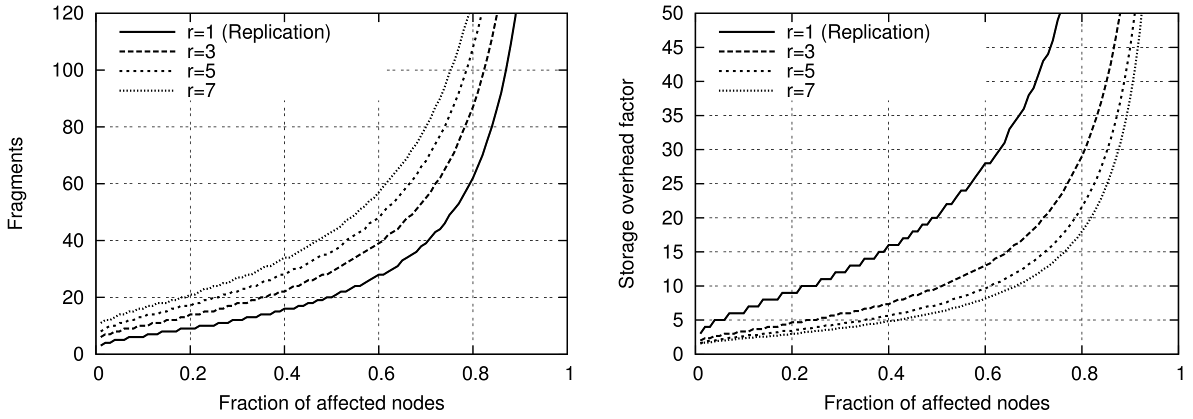


Figure 3. Number of fragments required for 99.9999% durability, and the resulting storage overhead.

5 Object aggregation

Glacier achieves data durability using massive redundancy. As a result, the number of internal objects Glacier must maintain is substantially larger than the number of application objects stored in Glacier. Each of these internal objects has a fixed cost; for example, each fragment is stored together with a manifest, and its key must be sent to other nodes during maintenance. To mitigate this cost, Glacier aggregates small application objects in order to amortize the cost of creating and maintaining fragments over a sufficient amount of application data.

In Glacier, each user is assumed to access the system through one node at a time. This node, which we call the user's *proxy*, holds the user's key material and is the only node in the system trusted by the user. All objects are inserted into Glacier from the object owner's proxy node. A user can use different proxy nodes at different times.

When a user inserts objects into Glacier, they are buffered at the user's proxy node. To ensure their visibility at other nodes, the objects are immediately inserted into Glacier's primary store, which is not aggregated. Once enough objects have been gathered or enough time has passed, the buffered objects are inserted as a single object into Glacier under an aggregate key. In the case of a proxy failure while an object is buffered, the next refresh operation will re-buffer the object for aggregation. Of course, buffered objects are vulnerable to large-scale correlated failures. If this is not acceptable, applications may invoke a `flush` method for important objects, which ensures that an aggregate with these objects is created and immediately stored in Glacier.

The proxy is also responsible for refreshing the owner's objects and for consolidating aggregates that contain too many expired objects. Performing aggregation and aggregate maintenance on a per-user basis avoids difficult problems due to the lack of trust among nodes. In return, Glacier foregoes the opportunity to bundle objects from different users in the same aggregate and to eliminate duplicate objects inserted by different users. In our experience, this is a small price to pay for the simplicity and robustness Glacier affords.

The proxy maintains a local *aggregate directory*, which maps application object keys to the key of the aggregate that contains the object. The directory is used when an object is refreshed and when an object needs to be recovered in response to an application request. After a failure of the proxy node, the directory needs to be regenerated from the aggregates. To do so, an owner's aggregates are linked in order of their insertion, forming a linked list, such that each aggregate contains the key of the previously inserted aggregate. The head of the list is stored in an application-specific object with a well-known key. To avoid a circularity, this object is *not* subject to aggregation in Glacier. The aggregate directory can be recovered trivially by traversing the list.

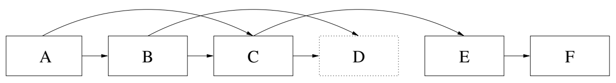


Figure 5. Reference graph. The object labeled 'D' has expired.

Aggregates are reclaimed in Glacier once all of the contained objects have expired. However, if aggregates expire in an order other than their insertion order, the aggregate list might become disconnected. To fix this problem, aggregates in the linked list may contain references to multiple other aggregates; thus, the aggregates actually form a directed acyclic graph (DAG, see Figure 5).

Glacier monitors the indegree of every aggregate in the DAG and tries to keep it above a fixed number d_{min}. If the indegree of an aggregate falls below this threshold, a pointer to it is added from the next aggregate to be inserted. This requires little extra overhead as long as insertions occur regularly; however, if a disconnection is imminent while no objects are inserted for an extended period of time, an empty aggregate may have to be created. This wastes a small amount of storage but, in our experience, occurs very rarely.

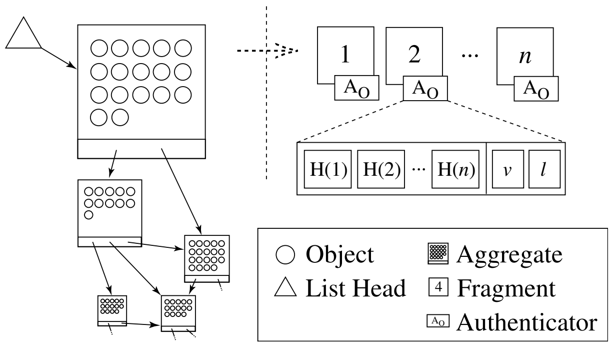


Figure 6. DAG of aggregates and the list head (left), and fragments of a single aggregate with the authenticator in detail (right).

An aggregate consists of tuples (o_i, k_i, v_i), where o_i is an object, k_i is the object's key, and v_i is the version number. Additionally, each aggregate contains one or more references to other aggregates. Note that the leases of the component objects are not stored; they are kept only in the aggregate directory, where they can be updated efficiently. The lease of the entire aggregate is the maximum of the component leases; for efficiency, Glacier tries to aggregate objects with similar leases.

5.1 Recovery

After a correlated failure, we must assume that all information that is not stored in Glacier is lost. In particular, this includes the contents of the primary store and, for most nodes, the aggregate directory.

The aggregate directory can be recovered by walking the DAG. First, the key of the most recently inserted aggregate is retrieved using a well-known key in Glacier. Then, the aggregates are retrieved in sequence and objects contained in each aggregate are added to the aggregate directory. The subleases of the component objects are set to the lease of the aggregate. Since aggregate leases are always higher than component leases, this is conservative. The primary store can either be repopulated lazily on demand by applications, or eagerly while walking the aggregate DAG.

Note that some of the references may be pointing to expired aggregates, so some of the queries issued to Glacier will fail. It is thus important to distinguish *actual* failures, in which at least $N-k+1$ fragment holders have been contacted but no fragments are found, from *potential* failures, in which some fragment holders are offline. In the latter case, recovery of the corresponding aggregate must be retried at a later time.

5.2 Consolidation

In order to maintain a low storage overhead, we use a mechanism similar to the segment cleaning technique in LFS [36]. Glacier periodically checks the aggregate directory for aggregates whose leases will expire soon, and decides whether to renew their leases. If the aggregate in question is small or contains many objects whose leases have already expired, the lease is not renewed. Instead, the non-expired objects are consolidated with new objects either from the local buffer or from other aggregates, and a new aggregate is created. The old aggregate is abandoned and its fragments are eventually garbage collected by the storing nodes.

Consolidation is particularly effective if object lifetimes are bimodal, i.e. if objects tend to be either short-lived or long-lived. By the time of the first consolidation cycle, the short-lived objects may have already expired, so the consolidated aggregate contains mostly long-lived objects. Such an aggregate then requires little maintenance, except for an occasional `refresh` operation.

6 Security

In this section, we discuss potential attacks against either the durability or the integrity of data stored in Glacier.

Attacks on integrity: Since Glacier does not have remote delete or update operations, a malicious attacker can only overwrite fragments that are stored on nodes under his control. However, each fragment holder stores a signed manifest, which includes an authenticator. Using this authenticator, fragment holders can validate any fragments they retrieve and replace them by other fragments if they do not pass the test. Assuming, as is customary, that SHA-1 is second pre-image resistant, generating a second fragment with the same hash value is computationally infeasible.

Attacks on durability: If an attacker can successfully destroy all replicas of an object in the primary store, as well as more than $n - r$ of its fragments, that object is lost. However, since there is no way to delete fragments remotely, the attacker can only accomplish this by either a targeted attack on the storage nodes, or indirectly by interfering with Glacier's fragment repair or lease renewal. The former requires successful attacks on $n - r$ specific nodes within a short time frame, which is highly unlikely to succeed due to the pseudo-random selection of storage nodes. The latter cannot go unnoticed because Glacier relies on secure and authenticated overlay communication for fragment repair and lease renewal. This leaves plenty of time for corrective action by system administrators before too many fragments disappear due to uncorrelated failures, churn or lease expiration.

Attacks on the time source: Since the collection process is based on timestamps, an attacker might try to destroy an object by compromising a time source such as an NTP server and advancing the time beyond the object's expiration time. For this reason, storage nodes internally maintain all timestamps as relative values, translating them to absolute values only during shutdown and when communicating with another node.

Space-filling attacks: An attacker can try to consume all available storage by inserting a large number of objects into Glacier. While this does not affect existing data, no new data can be inserted because the nodes refuse to accept additional fragments. Without a remote deletion primitive, the storage can only be reclaimed gradually as the attacker's data expires. To prevent this problem, incentive mechanisms [32] can be added.

Attacks on Glacier: If a single implementation of Glacier is shared by all the nodes, Glacier itself must be considered as a potential source of failure correlation. However, data loss can result only due to a failure in one of the two mechanisms that actually delete fragments, handoff and expiration. Both are very simple (about 210 lines of code) and are thus unlikely to contain bugs.

Haystack-needle attacks: If an attacker can compromise his victim's personal node, he has, in the worst case, access to the cryptographic keys and can thus sign valid storage requests. Existing data cannot be deleted or overwritten; however, the attacker can try to make recovery infeasible by inserting decoy objects under existing keys, but with higher version numbers. The victim is thus forced to identify the correct objects among a gigantic number of decoys, which may be time-consuming or even infeasible.

However, notice that the attacker cannot compromise referential integrity. Hence, if the data structures are linked (as, for example, the aggregate log), the victim can recover them by guessing the correct key of a single object. One way to facilitate this is to periodically insert reference objects with well-known version numbers, such as the current time stamp. Thus, knowledge of the approximate time of the attack is sufficient to recover a consistent set of objects.

7 Experimental evaluation

To evaluate Glacier, we present the result of two sets of experiments. The first set is based on the use of Glacier as the storage layer for ePOST, a cooperative, serverless email system [28] that provides email service to a small group of users. ePOST has been in use for several months and it has used Glacier as its data store for the past 140 days. The second set is based on trace-driven simulations, which permit us to examine the system under a wider range of conditions, including a much larger workload corresponding to 147 users, up to $1,000$ nodes, a wider range of failure scenarios and different types of churn.

The Glacier prototype is built on top of the FreePastry [21] implementation of the Pastry [37] structured overlay and makes use of the PAST [20] distributed hash table service as its primary store. Since the ePOST system relies on PAST for storage, Glacier now provides durable storage for ePOST.

7.1 ePOST experiments

Over time, our experimental ePOST overlay grew from 20 to currently 35 nodes. The majority of these nodes are desktop PCs running Linux; however, there are also machines running OS X and Windows. Our user base consists of 8 *passive* users, which are still primarily using server-based email but are forwarding their incoming mail to the ePOST overlay, and 9 *active* users, which rely on ePOST as their main email system.

ePOST uses Glacier with aggregation to store email and the corresponding metadata. For each object, Glacier maintains $N = 48$ fragments using an erasure code with $r = 5$, i.e. any five fragments are sufficient to restore the object. In this configuration, each object can survive a correlated failure of $f_{max} = 60\%$ of all nodes with probability $P_{min} = 0.999999$. We are aware of the fact that with only 35 nodes, our experimental deployment is too small to ensure that fragment losses are uncorrelated. Nevertheless, we chose this configuration to get realistic numbers for the per-node overhead.

Each of the nodes in the overlay periodically writes statistics to its log file, including the number of objects and aggregates it maintains, the amount of storage consumed locally, and the number and type of the messages sent. We combined these statistics to obtain a view of the entire system.

While working with Glacier and ePOST, we were able to collect much practical experience with the system. We had to handle several node failures, including kernel panics, JVM crashes and a variety of software problems and configuration errors. Also, there were some large-scale correlated failures; for instance, a configuration er-

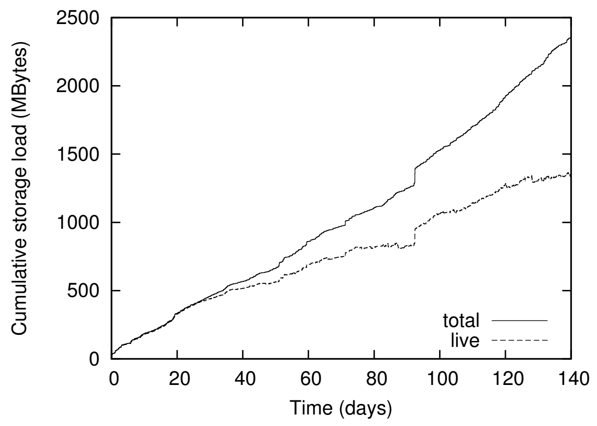


Figure 7. Storage load in ePOST.

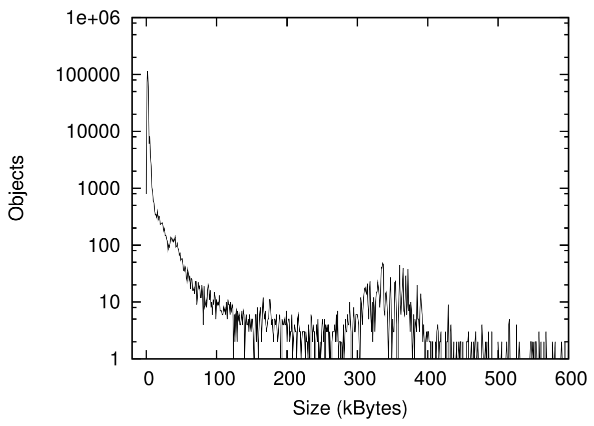


Figure 8. Object sizes in ePOST.

ror once caused an entire storage cluster of 16 nodes to become disconnected. Glacier was able to handle all of these failures. Also, note that Glacier was still under active development when it was deployed. During our experiments, we actually found two bugs, which we were able to fix simply by restarting the nodes with the updated software.

We initially configured Glacier so that it would consider nodes to have failed if they did not join the overlay for more than 5 days. However, it turned out that some of the early ePOST adopters started their nodes only occasionally, so their regions of key space were repeatedly taken over by their peers and their fragments reconstructed. Nevertheless, we decided to include these results as well because they show how Glacier responds to an environment that is heavily dynamic.

7.2 Workload

We first examined the workload generated by ePOST in our experimental overlay. Figure 7 shows the cumulative size of all objects inserted over time, as well as the size of the objects that have not yet expired. Objects are inserted with an initial lease of one month and are refreshed every day until they are no longer referenced.

Figure 8 shows a histogram of the object sizes. The histogram is bimodal, with a high number of small objects ranging between $1 - 10$kB, and a lower number of large objects. Out of the $274,857$ objects, less than 1% were larger than 600kB (the maximum was 9.1MB); these are not shown for readability. The small objects typically contain emails and their headers, which are stored separately by ePOST, while the large objects contain attachments. Since most objects are small compared to the fixed-size manifests used by Glacier (about 1kB), this indicates that aggregation can considerably increase storage efficiency.

7.3 ePOST storage

Next, we looked at the amount of storage required by Glacier to store the above workload. Figure 9 shows the combined size of all fragments in the system. The storage grows slowly, as new email is entering the system; at the same time, old email and junk mail is deleted by the users and eventually removed by the garbage collector.

In this deployment, garbage is not physically deleted but rather moved to a special trash storage, whose size is also shown. We used a lease time of 30 days for all objects. For compatibility reasons, ePOST maintains its on-disk data structures as gzipped XML. On average, this creates an additional overhead of 32%, which is included in the figures shown.

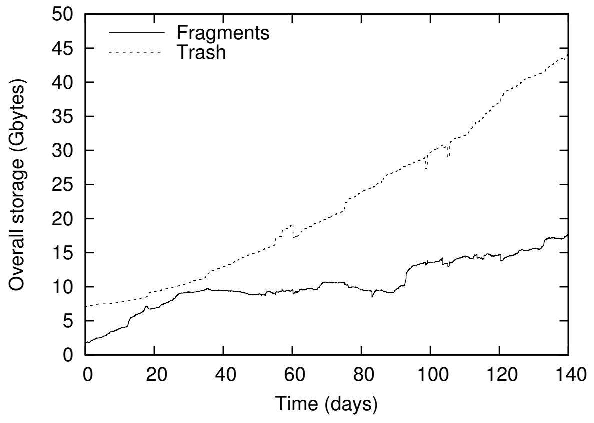


Figure 9. Storage consumed by Glacier fragments and trash.

Figure 10 compares the size of the on-disk data structures to the actual email payload. It shows the average number of bytes Glacier stored for each byte of payload, excluding trash, but including the 32% overhead from

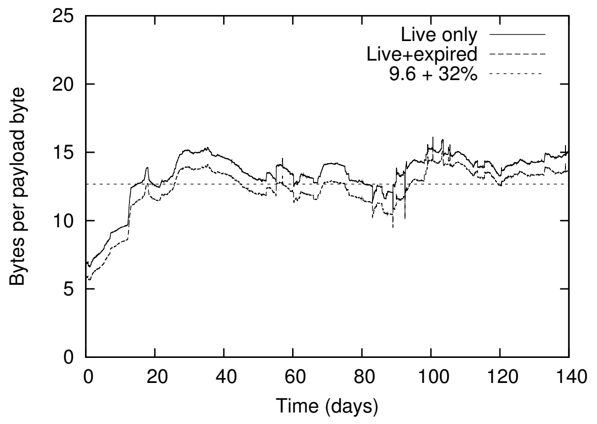


Figure 10. Storage factor, including serialization overhead.

XML serialization, for live data and for all data stored in Glacier. The average storage overhead over time is very close to the expected factor of 9.6 plus the 32% due to XML serialization.

7.4 ePOST traffic

Figure 11 shows the average traffic generated by an ePOST node in bytes and in Pastry-level messages sent per minute (the messages are sent over TCP, so small messages may share a single packet, and large messages may require multiple packets). For comparison, we also report traffic statistics for the other subsystems involved in ePOST, such as PAST and Scribe [11].

The traffic pattern is heavily bimodal. During quiet periods (e.g. days 30-50), Glacier generally sends fewer messages than PAST because it can mask short-term churn, but since the messages are larger because of the difference in storage factors (9.6 versus 3), the overall traffic is about the same. In periods with a lot of node failures (e.g. days 80-120), Glacier must recover the lost fragments by reconstructing them from other fragments, which creates additional load for a short time. The increase in Pastry traffic on day 104 was caused by an unrelated change in Pastry's leaf set stabilization protocol.

The traffic generated by Glacier can be divided into five categories:

- **Insertion:** When new objects are inserted, Glacier identifies the fragment holders and transfers the fragment payload to them.
- **Refresh:** When the leases for a set of objects are extended, Glacier sends the updated part of the storage manifest to the current fragment holders.
- **Maintenance:** Peer nodes compare their key lists, and lost fragments are regenerated from other fragments.
- **Handoff:** Nodes hand off some of their fragments to a new node who has taken over part of their key space.
- **Lookup:** Aggregates are retrieved when an object is lost from the object cache, or when small aggregates are consolidated into larger ones.

In Figure 12, the Glacier traffic is broken down by category. In times with a low number of failures, the traffic is dominated by insertions and refreshes. When the network is unstable, the fraction of handoff and maintenance traffic increases. In all cases, the maintenance traffic remains below 15 packets per host and minute, which is very low.

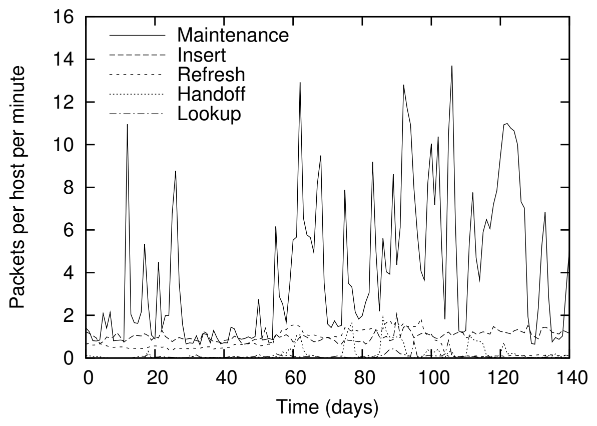
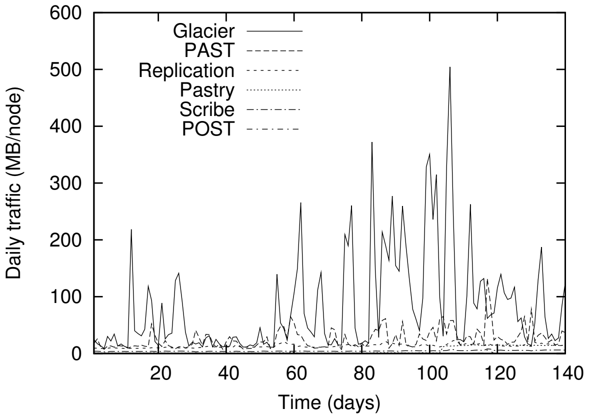


Figure 12. Messages sent by Glacier, by activity.

7.5 ePOST aggregation

To determine the effectiveness of aggregation, we also collected statistics on the number of objects and aggregates in the system. We distinguished between *live* objects, whose lease is still valid, and *expired* objects, which are still stored as part of an aggregate but are eligible for garbage collection.

Figure 13 shows the average number of objects in each aggregate. In our system, aggregation reduced the number of keys by more than an order of magnitude. Moreover, our results show that the number of expired objects remains low, which indicates that aggregate consolidation is effective.



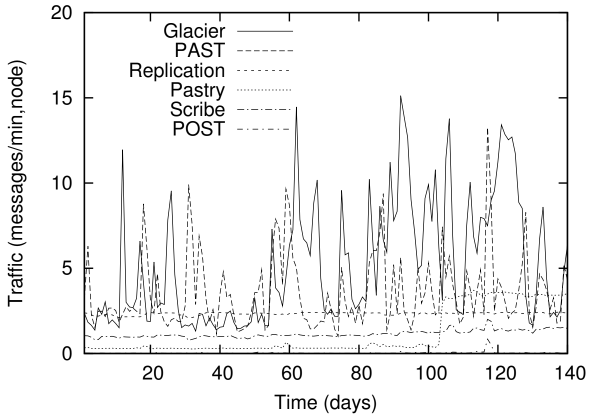


Figure 11. Average traffic per node and day (left) and average number of messages per node and minute (right).

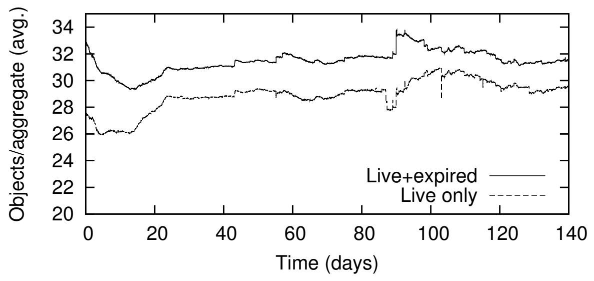


Figure 13. Aggregation factor.

7.6 ePOST recovery

To study Glacier's behavior in the event of a large-scale correlated failure, we randomly selected 13 of the 31 nodes in our experimental ePOST overlay and copied their local fragment store to 13 fresh nodes (note that, since our overlay has fewer than $N = 48$ nodes, some nodes store more than one fragment of the same object). The primary PAST store and the metadata were not copied. We then started a new Pastry overlay with only these 13 nodes. The resulting situation corresponds to a 58% failure in the main overlay, which is close to our assumed $f_{max} = 60\%$.

We then completely re-installed ePOST on a fourteenth node and let it join the ring. One of the authors entered his email address and an approximate date when he had last used ePOST. From this information, ePOST first determined the key of its metadata backup in Glacier by hashing the email address; then it retrieved the backup and extracted from it the root key of the aggregate DAG. The aggregation layer then reconstructed the DAG and restored the objects in it to the primary store. This process took approximately one hour to complete but could be sped up significantly by adding some simple optimizations. Afterwards, ePOST was again ready for use; all data that had been stored using Glacier was fully recovered.

7.7 Simulations: Diurnal behavior

For this and the following experiments, we used a trace-driven simulator that implements Glacier and the aggregation layer. Since we wanted to model a system similar to ePOST, we used a trace from our department's email server, which contains $395,350$ delivery records over a period of one week (09/15-09/21). Some email is carbon-copied to multiple recipients; we delivered each copy to a separate node, for a total of $1,107,504$ copies or approximately 8 GBytes. In the simulation, Glacier aggregates of up to 100 objects using a simple, greedy first-fit policy.

In our first simulation, we explore the impact of diurnal short-term churn. In their study of a large deployment of desktop machines, Bolosky et al. [8] report that the number of available machines, which was generally around approximately $45,000$, dropped by about $2,500$ (5.5%) at night time and by about $5,000$ (11.1%) during weekends. In our simulations, we modeled a ring of 250 nodes with the behavior from the study, where $M\%$ of the nodes are unavailable between 5pm and 7am on weekdays and $2M\%$ on weekends. The experiment was run for one week of simulation time, starting from Wednesday, 09/15, and the entire trace was used. Glacier was configured with the maximum offline time T_{max} set to one week.

Figure 14 shows how this behavior affects the total message overhead, which includes all messages sent over the entire week, for different values of M. As churn increases, fewer fragments can be delivered directly to their respective fragment holders, so insertion traffic de-

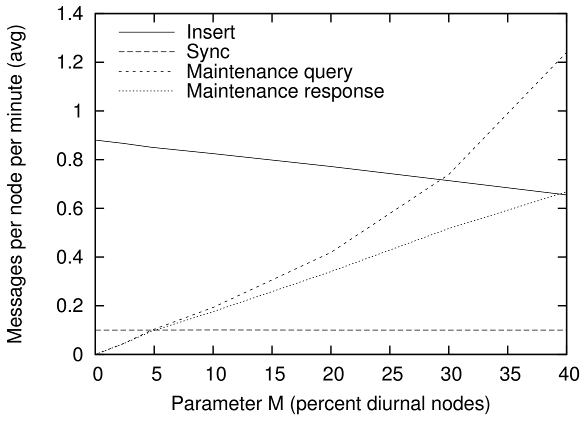


Figure 14. Impact of diurnal short-term churn on message overhead.

creases. However, the lost fragments must be recovered when the fragment holders come back online, so the maintenance overhead increases. As an additional complication, the probability that fragments are available at the designated fragment holder decreases, so maintenance requires more attempts to successfully fetch a fragment. This causes the disparity between maintenance requests and replies, which are shown separately in the figure.

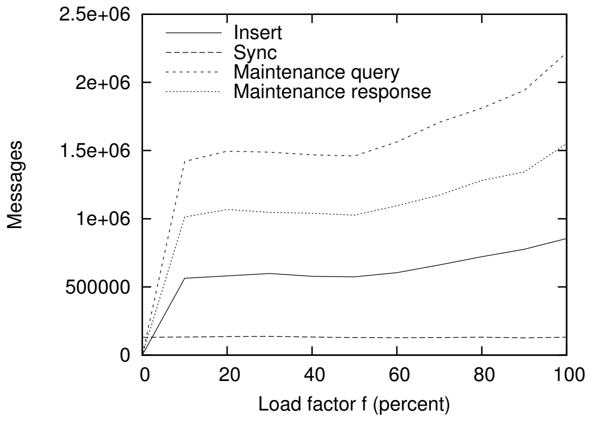


Figure 15. Impact of increasing load on message overhead.

7.8 Simulation: Load

In our second simulation, we study how the load influences the message overhead. We again used a overlay of 250 nodes and the trace from our mail server, but this time, we used only a fraction f of the messages. Instead of diurnal churn, we simulated uncorrelated short-term churn with a mean session time of 3 days and a mean pause time of 16 hours, as well as long-term churn with a mean node lifetime of 8 days. We varied the parameter f between 0 and 1.

Figure 15 shows how the load influences the cumulative message overhead over the entire week. Under light load, the message overhead remains approximately constant. This is because aggregates are formed periodically by every node, even if less than 100 objects are available in the local buffer. As the load increases further, the increase in overhead is approximately linear, as expected.

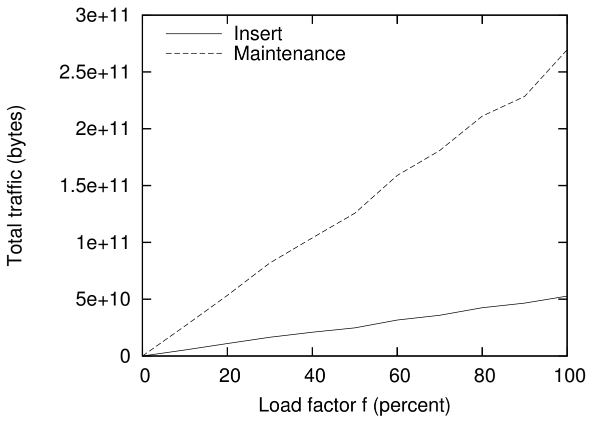


Figure 16. Impact of increasing load on total traffic.

Figure 16 shows the same overhead in bytes. Here, the threshold effect does not appear. Also, note the high maintenance overhead, as expected. This is due to the aggressive parameters we used for churn; at a node lifetime of eight days, almost all the nodes are replaced at least once during the simulation period, their local fragment store being fully regenerated every time. For their desktop environment, Bolosky et al. [8] report an expected machine lifetime of 290 days and low short-term churn, which would reduce the maintenance overhead considerably.

7.9 Simulation: Scalability

In our third simulation, we examine Glacier's scalability in terms of the number of participating nodes. We used the same trace as before, but scaled it such that the storage load per node remained constant; the full trace was used for our maximum setting of $N = 1000$ nodes. The churn parameters are the same as before.

Figure 17 shows the message overhead per node for different overlay sizes. As expected, the net overhead remains approximately constant; however, since query messages are sent using the Pastry overlay, the total number of messages grows slowly with $N \log N$.

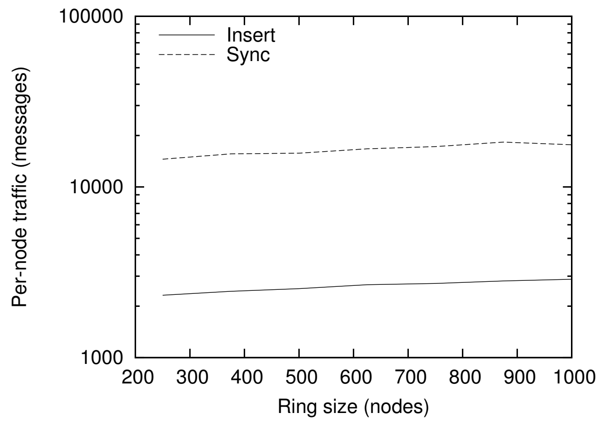


Figure 17. Message overhead for different overlay sizes and a constant per-node storage load.

7.10 Discussion

The storage overhead required to sustain large-scale correlated failures is substantial. In our experiments, we used fairly aggressive parameters ($f_{max} = 60\%$, $P_{min} = 0.999999$), which resulted in an 11-fold storage overhead. However, this cost is mitigated by the fact that Glacier can harness vast amounts of underutilized storage that is unreliable in its raw form. Moreover, only truly important and otherwise unrecoverable data must be stored in a high-durability Glacier store and is thus subject to large storage overhead. Data of lesser importance and data that can be regenerated after a catastrophic failure can be stored with far less overhead in a separate instance of Glacier that is configured with a less stringent durability requirement.

On the other hand, our experiments show that Glacier is able to manage this large amount of data with a surprisingly low maintenance overhead and that it is scalable both with respect to load and system size. Thus, it fulfills all the requirements for a cooperative storage system that can leverage unused disk space and provide hard, analytical durability guarantees, even under pessimistic failure assumptions. Moreover, our experience with the ePOST deployment shows that the system is practical, and that it can effectively protect user data from large-scale correlated failures. The ever-increasing number of virus and worm attacks strongly suggests that this property is crucial for cooperative storage system.

8 Conclusions

We have presented the design and evaluation of Glacier, a system that ensures durability of unrecoverable data in a cooperative, decentralized storage system, despite large-scale, correlated, Byzantine failures of storage nodes. Glacier's approach is 'extreme' in the sense that it does not rely on introspection, which has inherent limitations in its ability to capture all sources of correlated failures; instead, it uses massive redundancy to mask the effects of large-scale correlated failures such as worm attacks. The system uses erasure codes and garbage collection to mitigate the storage cost of redundancy and relies on aggregation and a loosely coupled fragment maintenance protocol to reduce the message costs. Our experience with a real-world deployment shows that the message overhead for maintaining the erasure coded fragments is low. The storage overheads can be substantial when the availability requirements are high and a large fraction of nodes is assumed to suffer correlated failures. However, cooperative storage systems harness a potentially huge amount of storage. Glacier uses this raw, unreliable storage to provide hard durability guarantees, which is required for important and otherwise unrecoverable data.

9 Acknowledgements

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