NEW APPLICATIONS OF DATA REDUNDANCY SCHEMES IN CLOUD AND DATACENTER SYSTEMS

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Data redundancy techniques such as replication and erasure coding have been studied in the context of distributed systems for almost four decades. This thesis discusses new uses of erasure coding and replication in the context of cloud computing and datacenter systems. It shows how erasure coding can be used to protect against vendor lock-in and how the interplay between replication and data sharding can mitigate the cost of configuration management.

BIOGRAPHICAL SKETCH

Hussam Abu-Libdeh was born in Ithaca, New York, in August of 1984. He grew up in Ramallah, Palestine, where he attended the Catholic School of Our Lady Annunciation. Upon graduation, he enrolled in Birzeit Universit in the West Bank. Due to the upheaval of the second Intifada, he dropped out of Birzeit a year later and relocated to Chicago, Illinois. He worked in Chicago for two years while taking classes at Moraine Valley Community College before transferring to the University of Illinois at Urbana-Champaign in 2004. He graduated with honors from the University of Illinois three years later with a degree in Computer Science and minors in Software Engineering and Mathematics. During his undergraduate studies, Hussam co-founded Kindi Software LLC– a byte-code obfuscation company— and worked in it until starting graduate studies in Distributed Computer Systems under the tutelage of Robbert van Renesse at Cornell University's Department of Computer Science.

To my mom and dad, Wafa and Hasan

and my siblings, Jafar, Haneen, and Hiba;

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CHAPTER 1

INTRODUCTION

Replication and erasure coding have been studied and compared extensively as two techniques for using data redundancy to build highly available distributed systems [34, 101, 119]. At its simplest, replication is the creation of multiple copies of a possibly mutating object with the intention of providing high availability or performance. The replicated object can be a record, file, application state, file system, an entire database, and so on. Processes that participate in a replication scheme are referred to as *replicas*. Replication has been discussed for four decades in database and distributed systems literature, and a variety of replication protocols have been developed for a variety of systems, environments, and objectives [43].

There are two general categories of replication protocols: *active replication* and *passive replication*. In active replication, also known as *state machine replication* [105], client operations are ordered by a protocol and forwarded to a collection of replicas that execute the operations independently, and in order. In passive replication, some times referred to as *primary backup replication*, one of the replicas is designated as a *primary*. It executes client operations and sends the resulting state updates to other replicas. These pure approaches have various advantages and drawbacks when compared with one another, and various hybrid solutions have been developed. For example, active replication cannot deal with non-deterministic processing and can waste computational resources if operations are compute-intensive. On the other hand, passive replication can waste network bandwidth if state updates are large, and it cannot mask the failure of a primary replica without detection and recovery, which may lead to performance degradation.

Replication protocols differ in replication degree (number of copies) and replica placement strategies, depending on their design goals. When replicating for high availability, replicas are assumed to fail independently and that is often achieved through diversifying the hardware and software stacks, as well as the network and power connections to the different replicas. On the other hand, when replicating for high performance, diversity is less important, and a higher degree of replication is favored in order to have a sufficient number of replicas to meet the load demands imposed on the replicated object.

Assumptions about the underlying environment model are another axis of differentiation between replication protocols. Some replication protocols assume a synchronous environment, with its bounds on message and processing delays; other protocols assume an asynchronous environment, with no such bounds. Similarly, some protocols assume bounds on clock drifts and others do not. Like synchrony assumptions, failure assumptions affect the complexity of protocols. A *fail-stop* model [104] assumes that processes follow their specification until they crash, after which, they don't perform any action, and their crash is eventually detected by all non-crashed processes that, in turn, do not suspect any non-crashed process of having crashed. This model makes strong assumptions, but it results in very simple protocols. Other models make weaker failure assumptions, resulting in more complex systems.

The computational complexity of storing and retrieving data is another tradeoff. Replication protocols store complete copies of replicated objects at the different replicas. This minimizes the computing cost at the expense of storage requirements. *Erasure coding* reduces storage cost by dividing an object into n fragments where m of which are sufficient to reconstruct it for $m < n$. This scheme tolerates the loss of any $n - m$ fragments of the data but comes with

the expense of creating fragments from objects and reconstructing objects from fragments.

In this thesis, we present new uses of redundancy schemes for systems running in datacenters and/or that rely on cloud computing services. The National Institute of Standards and Technology defines *Cloud computing* as a "model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction" [86]. Cloud service providers often manage warehouses, referred to as *dataceters*, with hundreds of thousands of machines. Access to these machines is offered as services in many forms, including infrastructure-as-a-service (storage, computation nodes, virtualized networks), platform-as-a-service (an integrated storage and computational framework), and application-as-a-service (such as hosted E-Mail and Customer Relation Management Systems). Cloud computing allows developers to harness the power of scalable, highly-available, infrastructure systems without having to invest time and money to build that infrastructure. Cloud computing, and its pay-as-you-go business model, gained wide-spread popularity with developers and organizations alike. Cloud computing has affected academic studies, and most of the literature published on distributed systems today targets cloud computing and datacenter settings.

These environments exhibit many of the traits of environments that have been studied extensively in the past, but they also add unique characteristics. In this thesis, we are interested in the economic factors of cloud computing introduced by competing vendors and the pay-as-you-go business model, as well as ubiquitous use of horizontal scaling via data partitioning (henceforth referred

to as *data sharding*). In subsequent chapters we discuss the use of erasure coding to protect against cloud-storage vendor lock-in, and we exploit the ubiquitous use of sharding in datacenter services to avoid centralized configuration management services.

CHAPTER 2

BACKGROUND

To put the discussion in context, we first present some background. Additional related work is discussed in the other chapters.

2.1 Erasure Coding

Erasure coding is a forward error correction code that provides fault tolerance and prevents data loss without the overhead of full replication [45, 56, 98, 119]. There are three types of erasure-codes: optimal, near optimal, and rateless. Optimal erasure-codes, such as Reed-Solomon [38, 93, 99], encode an object into n *fragments*, any m of which are sufficient to reconstruct the object ($m < n$). We call $r = \frac{m}{n} < 1$ the *rate* of encoding. A rate r optimal erasure-code increases the storage cost by a factor of $\frac{1}{r}$. For example, an $r = \frac{1}{4}$ encoding might produce $n = 64$ fragments, any $m = 16$ of which are sufficient to reconstruct the object, resulting in a total overhead factor of $\frac{1}{r} = \frac{n}{m} = \frac{64}{16} = 4$. Note that $m = 1$ represents full replication; and RAID level 5 [92] can be described by ($m = 4$, $n = 5$). Unfortunately, optimal erasure-codes are costly (in terms of memory usage and/or processor time) when m is large, so near optimal erasure codes such as Tornado codes [81, 82] are often used. These near optimal erasure-codes require (1+ϵ)m fragments to recover the data object. Reducing ϵ can be done at the cost of increasing processor time. Alternatively, rateless erasure codes such as LT [80], Online [85], or Raptor [107], codes transform a data object of m fragments into a practically infinite encoded form. We assume the use of optimal erasure-codes unless otherwise noted.

Weatherspoon and Kubiatowicz illustrated that large numbers of fragments provide greatly increased durability [119]. More importantly, using erasure-

coding instead of replication can reduce network bandwidth and storage capacity requirements by an order of magnitude without compromising data durability or availability [33,37,119].

However, there are negative consequences to using erasure-codes. Erasure-codes and their checksum [120] are expensive to produce. For example, Pond's [97] performance was limited by erasure-coding; producing erasure-encoded fragments contributed more than 72% (566.9 ms out of 782.7 ms for a 2MB update) of the write latency. So there is a tradeoff between CPU costs and network efficiency when considering between erasure-codes and replication. Additionally, if a metadata layer individually accounts for each fragment, this layer can be overloaded with location pointers. In order to prevent this problem, fragments need to be aggregated (e.g. extents), so their individual cost can be amortized. Further, repair is more complicated with erasure-codes, since a complete data object would have to be reconstructed to produce a new fragment for repair. This repair read adds extra complexity and cost to the erasure encoded system. However, reconstructed data objects can be cached to reduce costs (eliminate read requirement) of subsequent repairs.

2.2 Replication

Modern datacenter services rely primarily on two approaches to replication: Primary-backup and quorum intersection protocols. Primary-backup [22,40] is used in systems such as GFS and HDFS [62,109]. A primary replica receives all updates, orders them, and forwards them in FIFO order to the non-faulty backup replicas. In case of an unresponsive primary, another replica may become primary following reconfiguration by a configuration management service. If the original primary was mistakenly suspected of having failed, a client

may read the result of some update operation to the original primary that is not applied, and never will be, to the new primary, resulting in *divergence*. In order to avoid divergence, clients track the current active configuration as maintained by the configuration manager.

Quorum intersection protocols are particularly useful for `put/get`-type Key-Value Stores such as Amazon's Dynamo and Apache Cassandra [53, 73]. In these, a `put` operation, accompanied by a timestamp, is sent to a "`put`-quorum," while a `get` operation reads from a "`get`-quorum" (and returns the result with the highest timestamp). By making quorums smaller than the entire set of replicas, availability and performance are achieved. By guaranteeing that any `put`-quorum and `get`-quorum intersect, a `get` can be guaranteed to see the latest completed `put` operation. However, divergence can still occur in the case of dynamic reconfiguration of replicas as quorums may temporarily fail to intersect [53].

2.3 Strong Consistency

A *memory consistency model* formally specifies how a system appears to programmers, and restricts what values can be returned by a read operation in a shared-memory program execution [20]. Weak consistency models make few (if any) restrictions or guarantees, and are often phrased in terms of "in the lack of future updates, the system will eventually ...". While weak consistency models have enabled the large-scale distributed systems of today's cloud computing environments, such guarantees are not suitable for all applications. So, developers go to extraordinary lengths to work around weak consistency guarantees [17, 108].

In this thesis, chiefly in Chapter 4, *linearizable consistency* is used as the strong consistency model. Linearizable consistency stipulates that all operations ap-

pear to clients to have executed between the real time of their invocation and when they receive a response [68]. Strong consistency protocols often rely on majority voting techniques, where $2f + 1$ replicas are required to tolerate f failures. Using $2f + 1$ replicas, as is the case in Paxos and Quorum Replication systems, is not only expensive in terms of resources, but it is also harder to ensure that the larger number of replicas fail independently. Also, reconfiguration—important to service expansion, migration, or software updates in the cloud—is difficult while maintaining strong consistency.

2.4 Reconfiguration

Deployment parameters, such as machine address, port numbers, file paths, disk mount points, protocol parameters..., are collectively referred to as a configuration of the system. For the purposes of our discussion in Chapter 4, the *configuration* of a distributed system describes the list of replicas in a replicated system. A replicated system is often *reconfigured* in order to change its replicas, remove faulty ones, or insert new replicas.

In cloud services, using coordination services or lock services as centralized configuration services, such as Chubby [41] and ZooKeeper [69], is increasingly common.

2.5 Failure Detection

Some simple replication protocols, e.g., Primary-backup, assume a fail-stop model with perfect failure detection [114]. In practice, timeouts are often used to detect failures in these protocols, and the choice of timeout values involves a trade-off between the liveness and safety of the system.

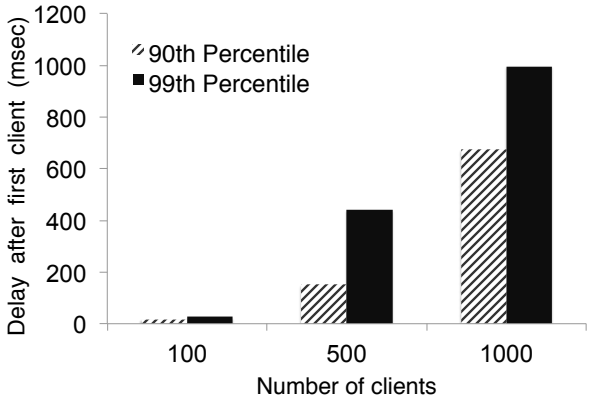


Figure 2.1: ZooKeeper client notification delay

Even with a centralized configuration manager, like Zookeeper or Chubby, there could be a delay until all clients learn of a new configuration, as demonstrated in Figure 2.1. In this experiment, we used Zookeeper to manage the configuration of a replicated service, forced a configuration change, and measured the latency until 90% and 99% of the clients get notified of the new configuration after the first client is notified. Late notifications about changes could result in inconsistencies, if clients interact with a defunct primary or an old replica.

2.6 Terminology

In this thesis we use the terms *node* and *server* synonymously. A *process* is a program executing on a server. A *replica* is a process that is executing a replication protocol. In the discussion of replication protocols, all four terms (node, server, process, replica) will be used synonymously. In a running system, different replicas might be running on the same physical machine. This lessens the failure-tolerance of the system, as these collocated replicas are not *failure-independent*; a failure in the physical machine might cause both replicas to fail.

CHAPTER 3

USING ERASURE CODING TO AVOID VENDOR LOCK-IN

An increasing number of companies and organizations are migrating data to cloud storage providers [111]. Examples include: Storing online users' account data, off-site backup storage, and content distribution. One impressive pilot program and motivating example is the United States Library of Congress's move its digitized content to the cloud [21]. Other participants in that program include the New York Public Library and the Biodiversity Heritage Library.

For a service to depend solely on a particular cloud storage provider brings risks. Even though different cloud storage providers offer nearly identical commodities, customers can experience *vendor lock-in*: It can be prohibitively expensive for a client to switch from one provider to another. Storage providers charge clients for each request, inbound/outbound transfer bandwidth, as well as for hosting the actual data. Thus, a client moving from one provider to another pays for bandwidth twice, in addition to the actual cost of online storage. This doubled cost of moving data leads to a kind of *data inertia*; the more data stored with one provider, the more difficult it becomes to move to another provider. This cost must be taken into consideration by consumers of cloud storage, lest they be locked-in to less-than-ideal vendors after entrusting them with their data. The resulting vendor lock-in gives storage providers leverage over clients with large amounts of data. In particular, clients can become vulnerable to price hikes by vendors, and will not be able to cheaply move to new and better options when they become available. The quickly-evolving cloud storage marketplace makes this concern more real: Today's best decision may leave the customer trapped with an obsolete provider later due to vendor lock-in.

In addition to possible increased costs, vendor lock-in subjects customers to the possibility of data loss if a provider goes out of business or suffers a catastrophe. Even though cloud operators commit to strict service-level agreements (SLAs) [3, 10, 16] with impressive up-times and response delays, failures and outages do occur [2, 15]. Recent incidents have shown how failures at cloud providers can result in mass data loss for customers, and that outages can last up to several hours [6].

Since cloud storage is, for the most part, a commodity, customers can guard against vendor lock-in by replicating data at multiple providers. This approach, however, incurs high storage and bandwidth costs. A more economical approach is to spread the data across multiple providers and introduce redundancy to tolerate possible failures or outages, but stopping short of full replication. This is similar to what has been done for years with disks and file systems. For example, the Redundant Array of Inexpensive Disks (RAID) technology stripes data across an array of disks and maintains parity data that can be used to reconstruct the contents of any individual failed disk.

In this chapter we argue that similar techniques should be employed with to cloud storage, although the failure model differs somewhat. We describe RACS (Redundant Array of Cloud Storage), a cloud storage proxy that transparently stripes data across multiple cloud storage providers. RACS reduces the one-time cost of switching storage providers in exchange for additional operational overhead. RACS assumes a small storage interface (`put, get, delete, list`) and exposes that interface to its applications.

This system makes several contributions. We show through simulation and real-life pricing models that, through careful design, it is possible to tolerate outages and mitigate vendor lock-in with reasonable cost overhead. We also show

the cost of switching cloud storage vendors for a large organization through trace-driven simulation. Finally, we build and evaluate a working prototype of RACS that is compatible with existing Amazon S3 clients and is able to use multiple storage providers as back-ends; we then demonstrate its effectiveness on end-user traces.

3.1 Why Diversify?

Hosted data storage is a commodity, and it is fungible. Certainly, cloud storage providers *do* distinguish themselves by offering services above-and-beyond basic storage. Often, these services involve integration with other cloud computing products; for example, Amazon's EC2 and Cloudfront are deeply intertwined with S3. But many consumers just want reliable, elastic, and highly available online storage. Because of this, cloud storage providers aggressively compete on price, knowing that price will be the ultimate deciding factor for many consumers. Providers also compete on guarantees of uptime and availability, in the form of SLAs. These guarantees are satisfied by systems meticulously designed to handle load balancing, recurring data backup, and replication to handle component failures seamlessly. So one could understandably question if there's really any benefit to be had by adding even more redundancy to the system and spreading data across multiple providers.

To address this question, we distinguish between two different kinds of failures:

Outages: Hardware or software failures, misconfigurations, or unfortunate events leading to data loss in the cloud. As mentioned, cloud providers already offer strong protection against component failures, so there is a weak case for adding another safety measure on top of cloud storage sys-

tems. Still, it does happen occasionally that an outage strikes the cloud; for instance, a failure in October 2009 at a Microsoft data center resulted in data loss for many T-Mobile smart phone users [70].

Economic Failures: We define *economic failure* to be the situation where a change in the marketplace renders it prohibitively expensive for a cloud storage consumer to continue to use a service. For example, prior to June 30, 2010, there were no bandwidth charge for uploading data to Amazon S3. But on June 30, 2010, Amazon started charging fifteen cents per gigabyte. A customer who relies on a heavy volume of uploads, such as an online backup business, might find this change too costly to maintain a profitable business.

We focus the discussion in this chapter primarily on economic failure.

3.1.1 Avoiding storage-vendor lock-in

Cloud storage services differ in price and performance. Some providers charge a flat monthly fee, others negotiate contracts with individual clients, and still others offer discounts for large volume as temporary promotional incentives, or for off-peak hours. Some providers may be desirable for geographic reasons (Amazon offers different zones for the United States, Europe, Asia Pacific, and South America), and others might offer extra features, such as publishing files directly to the web or access via mountable file systems. Changes in these features, and emergence of new providers with more desirable characteristics, could incentivize a client to switch from one storage service to another. However, because of data inertia, clients may not be free to choose a better vendor, due to prohibitively high costs in switching from one provider to another. This

puts the client at a disadvantage when a vendor raises prices or negotiates a new contract.

Consider a situation where a new provider with a low pricing scheme emerges on the market. A client at an old storage service provider has to make an all-or-nothing decision about that service. The client either moves all its data to the new provider and incurs the cost of switching to gain the benefit of lower prices, or it stays at the old provider and saves the cost of switching with the risk of incurring higher costs in the long run. The problem, of course, is that the client cannot predict the future, so the client cannot know if and when the current provider will lower prices to compete with the other providers. From the client's view, a premature switch can be worse than not switching, and a late switch might have lost its value. Of course, this dilemma is not limited to price changes. Clients might remain with an under-performing provider simply because switching to better providers is deemed too costly.

One way to facilitate client agility for responding to provider changes is to make switching and data placement decisions at a finer granularity than all-or-nothing. This fine granularity can be achieved by striping the client's data across multiple providers. For example, if a client spreads data across several providers, then taking advantage of a new fast provider entails switching only a fraction of the data, which could be more attractive economically.

Of course, striping data across multiple providers adds costs, due to pricing differences between providers. However, as we show below, the differences are low and can be mitigated by choosing clever striping schemes.

3.1.2 Incentives for redundant striping

We have argued that striping data across multiple providers facilitates client agility. We now argue that by adding redundancy to data striping, clients can maintain this mobility while protecting against outages.

Below is a brief description of what clients gain from erasure coding across multiple providers:

- **Tolerating Outages**. Although storage providers offer highly available services, even the best providers suffer occasional mishaps. Inopportune outages can last for several hours [2,6,15] and can result in severe financial losses for the providers and consumers of the storage service. Data redundancy across multiple providers allows clients to mask temporary outages and get higher data availability.
- **Tolerating Data Loss**. Storage providers implement internal redundancy and replication schemes to avoid accidental data loss. However, recent experience shows that hosted data could still be lost [70]. Storing redundant data copies at multiple, failure-independent, storage providers allows consumers to mask the failure of, or data loss at, any individual providers.

  A simple way to tolerate provider failure is by replicating data at multiple providers. However, this approach is costly, since the overhead per replica is 100% the size of the data. A more economically sensible approach is to lower the redundancy overhead by using erasure coding and striping the data (and redundant) blocks across multiple providers to tolerate the failure of one or more of them.
- **Adapting to Price Changes**. Redundancy via erasure coding allows clients to make migration decisions at a lower granularity. For example,

clients can adapt to changes in storage providers' prices by fetching erasure coded data fragments from cheaper providers. If a provider becomes too expensive, clients can avoid reading from it and reconstruct its data from the redundancy at other locations.

- **Incorporating New Providers**. If a new service provider enters the market, clients can include it in future erasure codes.
- **Controling Spending**. Second-tier cloud storage providers, such as DreamHost's DreamObject [7], offer low-priced storage at lower performance, compared to leading cloud storage providers such as Amazon's S3, Windows Azure Storage, and Rackspace Cloudfiles. By using a mixture of leading providers, second-tier storage services, and local servers, clients can control the cost of storing and serving data. For example, second-tier storage services might not be powerful or reliable enough to handle the entirety of the storage load, but by storing redundant copies of data on them, clients can use them in some accesses in order to lower the overall cost of storage.
- **Choice in Data Recovery**. In the event of a failure of one or more online storage providers, redundancy gives clients multiple strategies for recovering the lost data. For example, clients might choose to reconstruct the missing data from some providers but not others. Another approach is to reconstruct the data lazily, by reconstructing missing data only in response to client requests. Or, if the degree of redundancy is sufficient, clients might even choose to ignore the failed provider and continue operation without reconstruction.

In short, if clients use a single provider, then they would not be able to tolerate that provider's failure. Replicating data to multiple providers allows clients

`put`	*bucket*, *key*, *object*
`get`	*bucket*, *key*
`delete`	*bucket*, *key*
`create`	*bucket*
`delete`	*bucket*
`list`	keys in *bucket*
`list`	all buckets

Table 3.1: Amazon S3 operations

to tolerate failures, but at a high cost. In comparison, erasure coding and striping data across multiple providers allows clients to tolerate provider failures at a lower cost than replication. Additionally, data redundancy across storage providers allows clients to implement different strategies and optimize for different objectives in storing and accessing data.

3.2 Design

RACS exports an interface similar to Amazon S3 which stores data in named *buckets*. Each bucket is a flat namespace, containing *keys* and the associated *objects*. A bucket cannot contain other buckets. Objects can be of arbitrary size, up to 5 gigabytes. Partial writes to objects are not allowed; objects must be written in their entirety, but partial reads are allowed. We chose to export Amazon S3's interface for two reasons; first, it is simple and easy to work with. Second, its popularity means that existing client applications can use RACS. In what follows, we discuss how RACS implements the core subset of S3's operations, shown in Table 3.1.

S3 exports two remote procedure call APIs: SOAP and REST, which use standard HTTP headers and commands. RACS implements only the REST API, which is more widely used, but there is no reason it could not be extended to provide a SOAP interface. Most S3 clients have the option to specify a proxy;

RACS can be used transparently with these applications, by specifying proxy and authentication information.

RACS operates as a proxy interposed between the client application and a set of n *repositories*, which are cloud storage locations ideally hosted by different providers. Upon receiving a `put` request, RACS uses erasure coding to split the incoming object into n fragments, each of size $\frac{1}{m}$, such that only $m < n$ fragments are required to reconstruct the object—m, n are configurable parameters. The bucket and key associated with the object in the original `put` request are associated with each of the n fragments to create n *shares*. Each share is sent to a different repository.

When a client issues a `get` request, RACS fetches m shares and reconstructs the object. Metadata such as bucket and key names, modification times, and MIME types are replicated across all servers as part of the shares; these data are small and replication costs are not prohibitive unless the workload is dominated by very small objects. RACS also stores a small amount of its own metadata with each share, including the size of the original object and its content hash. This allows `list` requests, which return information including size and MD5 sum for every key in a bucket, to be satisfied without querying multiple repositories or reconstructing coded objects. An object metadata is generated whenever a `put` operation is invoked. The metadata is included in all of the `put` object shares to be stored at all storage providers. RACS does not support direct modification of metadata. Figure 3.1 illustrates the RACS architecture with a single proxy.

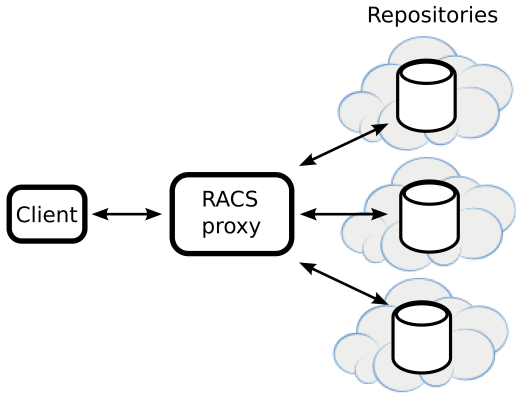


Figure 3.1: RACS single-proxy architecture

3.2.1 Distributed RACS

Because all data must pass through a RACS proxy to be encoded and decoded, a single RACS proxy could easily become a bottleneck. To avoid this, RACS is run as a distributed system, with many proxies concurrently communicating with the same set of repositories. RACS proxies store a limited amount of shared state: User authentication information and the location and credentials for each repository. Changes to this state are broadcast to each proxy. Distributing shares of data to multiple repositories introduces a data race that is not native to S3 semantics. If two clients simultaneously write to the same key using Amazon S3, Amazon will process the writes in the (arbitrary) order it receives them, and the later write will trump the earlier. If the same two writes are issued to two different RACS proxies, then this race will occur at each of the n repositories, with possibly catastrophic results. In particular, any two repositories for which the outcome of the race differs will become inconsistent, and RACS would not be able to determine which of the two objects is correct. Worse, there might no longer be m shares of either object in the system, leading to data loss. A related problem occurs when a read and write happen concurrently; the read may return some combination of old and new shares. To prevent these races, RACS

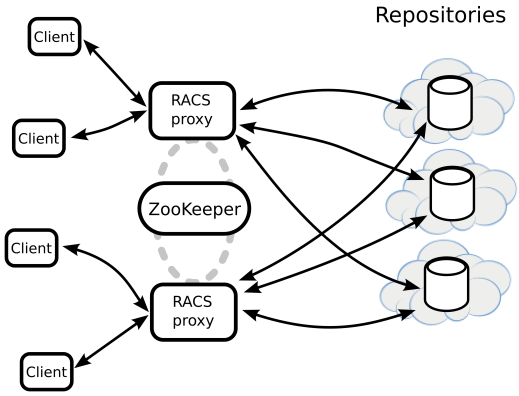


Figure 3.2: RACS multi-proxy architecture

proxies coordinate by using one-writer, many-reader synchronization for each *(bucket,key)* pair. RACS relies on Apache ZooKeeper [19] for these distributed synchronization primitives. ZooKeeper is a distributed system that provides atomic operations for manipulating distributed tree structures; it can be used to implement synchronization primitives and abstract data types (ADTs). Such synchronization primitives cannot be built using only S3 because it lacks strong consistency guarantees. Figure 3.2 illustrates the RACS architecture with multiple distributed proxies.

3.2.2 Failure recovery

Economic failures, such as price increases, are often announced ahead of time. Therefore, administrators of a RACS system can begin a *migration* away from a given repository even before the failure occurs. During such a migration, RACS moves shares from the soon-to-fail repository to a fresh repository. While migrating, RACS does not access the failed repository to serve `get` requests unless other failures have occurred. `put` requests are also redirected from the failed repository to the new repository. If the failures were not announced ahead of time, RACS must reconstruct the shares stored on failed repositories from shares

on other repositories. This is still preferable to replication, though, as only $1/n$ of the total number of shares is recreated for each failed repository, instead of a full copy in the case of replication. Depending on configuration, RACS may treat all failures as transient, and continue normal operation in the hope that failed repository returns. Operations such as `put` and `delete` that modify data during such an outage will cause the failed repository to diverge from the others; we leave the question of how to recover a repository from a transient outage for future work.

3.2.3 Policy hints

RACS is compatible with unmodified S3 client applications. However, a RACS-aware client can include in its requests hints about how RACS should behave. Many RACS operations involve a choice about which repositories to communicate with, and in which order. Using *policy hints*, a client can specify preferred repositories. This has many potential uses: Exploitation of geographic proximity, navigation of variable pricing schemes (such as off-peak discounts), cost-balancing, or even load-*un*balancing to favor inexpensive repositories. Further, trade-offs may be made to favor bandwidth over latency or vice versa. For example, a `list` operation normally queries only a single repository, but clients who value latency above all else might choose to concurrently query all repositories and take the quickest answer.

3.2.4 Repository adapters

Different cloud storage providers expose different APIs. For the providers that do not expose S3's interface that RACS implements, developers must write

adapters, also called *shims*, to translate between the APIs. For some providers, such as Rackspace, there is a direct correspondence to S3 operations. For others, such as network mounted filesystems, a more complicated mapping must be devised.

3.2.5 Performance overhead

The primary goal of RACS is to mitigate the cost of vendor lock-in by reducing the importance of individual storage providers. In exchange, RACS incurs higher overhead costs, as follows:

Storage. RACS uses a factor of $\frac{n-m}{m}$ more storage for the redundant $(n - m)$ shares, plus some additional overhead for metadata associated with each share. Since storage is split among different providers, some of whom may have higher rates, the total price paid for storage may be greater than $\frac{n}{m}$ times the cost of using only the least expensive provider.

Number of requests. RACS issues a factor of n more requests to repositories for `put` , `create` , and `delete` operations than the client would using S3 directly. `get` requests are multiplied by m. `list` operations do not use any additional requests by default.

Bandwidth. RACS increases the bandwidth used by `put` operations by a factor of $\frac{n-m}{m}$, due to the redundant $(n - m)$ shares. `get` requests do not incur a commensurate bandwidth increase. `list` uses no additional bandwidth by default. However, each operation does require slightly increased bandwidth, added requests per operation and the size of the header for each request; this cost might be significant if relatively small objects are stored.

Latency. RACS may introduce slightly higher latency for `put` requests, as `put` operations must wait for the slowest of the repositories to complete. On the other hand, operations such as `list` that require only one answer can optionally query all repositories in parallel and return as soon as the first response is received. However, there is an inherent tradeoff between bandwidth and latency. `get` occupies a middle-ground: Depending on which subset of m repositories is queried, latency could be better than the average of all repositories. Erasure coding also introduces latency, since the proxy must buffer blocks of data to encode or decode. Coordination with ZooKeeper is another source of latency, although it is expected to be little more than the round-trip time to ZooKeeper except in the presence of object contention.

3.2.6 RACS prototype implementation

Our RACS prototype is implemented in approximately 4000 lines of Python code. Most existing S3 REST clients can be configured to communicate with S3 through an HTTP proxy; this is generally used to bypass firewalls. By setting RACS as a proxy, S3 clients can take advantage of RACS without modification. It is relatively easy to map a basic data model onto others; we might have instead chosen to have RACS present itself as a network file system, but using file system semantics would have added considerable complexity to the implementation. Our prototype does not yet implement the complete S3 interface: It has no provisions for authentication or payment-related queries. It also does not implement RACS policy hints, although a static configuration option can be set to prioritize bandwidth or latency. ZooKeeper is used to implement readers-writer locks at per-key granularity for distributed RACS proxies.

The design for RACS calls for repositories backed by many different storage providers. Our implementation supports three kinds of repositories: S3-like (including S3 and Eucalyptus [89], an open-source Amazon Web Services clone), Rackspace Cloud Files [14], and a file system mapping that can be used for mounted network file systems. The Rackspace repository adapter is 258 lines of Python code, and the file system adapter is 243. Both were written in a matter of hours; we expect this level of effort to be typical for adding new kinds of repositories.

The RACS source code is published under the BSD license and is freely available at `http://www.cs.cornell.edu/projects/racs`

Before evaluating our prototype, we first estimate the vendor lock-in cost associated with switching storage providers. We then estimate the cost of avoiding vendor lock-in by using RACS.

3.3 An Internet Archive in the Cloud

One of our motivating examples is the recent decision by the Library of Congress and a handful of other American public libraries to move their digitized content to the cloud [21]. A pilot program of this initiative is being developed by the non-profit DuraSpace organization [8]. Publicly released documents, along with personal conversations with the program directors, reveal that the project (titled DuraCloud) entails replicating the libraries' data across multiple cloud providers to safeguard against sudden failure. We believe that RACS' data striping approach is more fit for the task because it minimizes the cost of redundancy and allows a large organization to switch cloud storage providers without incurring high costs.

We used a trace-driven simulation to predict the costs associated with hosting large digital libraries in the cloud. Our trace covers 18 months of activity on the Internet Archive [12] (IA) servers. The trace represents HTTP and FTP interactions to read and write various documents and media files (images, sounds, videos) stored at the Internet Archive and served to users. We believe this trace is a good reflection of the type of workloads induced on online digital library systems, both in terms of the file sizes and request patterns.

Our goal from using this trace is to answer the following high-level questions:

- What are the predicted costs associated with storing library-type content, such as the Library of Congress and the Internet Archive, on the cloud?
- What is the predicted cost of changing storage providers for large organizations? What is the predicted added cost of a DuraCloud-like scheme?
- What is the predicted cost of avoiding vendor lock-in using RACS? And what is the predicted added cost overhead of using RACS?

Our collaboration with the Internet Archive took place in 2010. Since then, new cloud storage providers have entered the business, with new services and pricing structures. We have not been able to run our analysis on newer traces, but we have updated but our pricing scheme to reflect today's market.

3.3.1 Trace characteristics

The Internet Archive trace covers the period from November of 2007 to May of 2009. Figure 3.3 shows how much data is written to the Internet Archive servers and read back. The volume of data transfers is dominated 1.6:1 by reads to writes. Figure 3.4 shows the number of read and write requests issued to

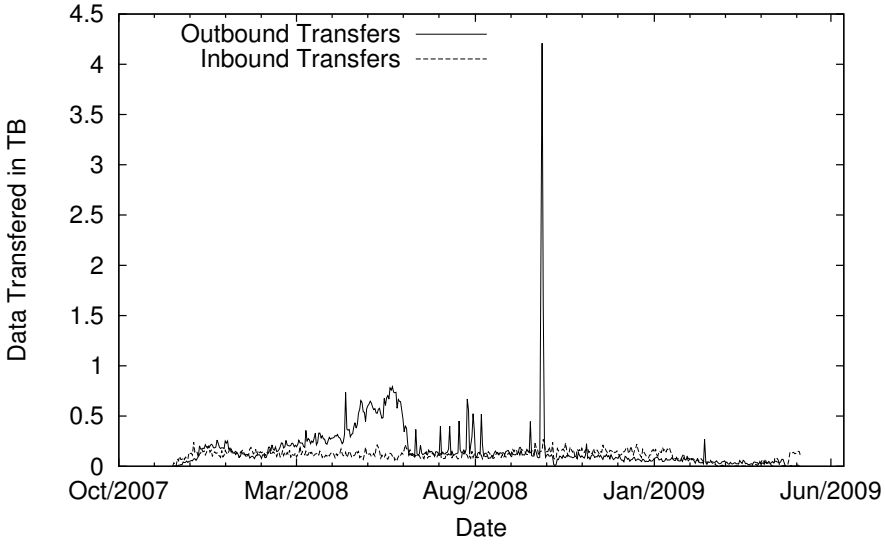


Figure 3.3: Inbound and outbound data transfers in the Internet Archive trace

the Internet Archive servers during that period. Read requests are issued at a 2.8:1 ratio compared to write requests. It is important to note that while this trace does not represent read/write patterns for an online library, it does reflect patterns of accessing archived information. We could not obtain traces from an online library, but we expect the patterns to be similar to the Internet Archive trace because they both reflect access to historical documents and multimedia. Another disclaimer, while the trace was current at the time of conducting this study, it is 5 years old at this point. While we do not expect the access patterns for historical and archival data to be very different today, it is important to remember things might have changed. It would be interesting to revisit this analysis with more up-to-date traces.

In our simulation, we assume that the cloud is not preloaded with any data before the simulation begins. This does not result in warm-up bias, however, because clients of a cloud storage provider are charged monthly for the total data stored online at the provider, and the bandwidth consumed in responding to data access requests in that month. Thus, starting the simulation with empty

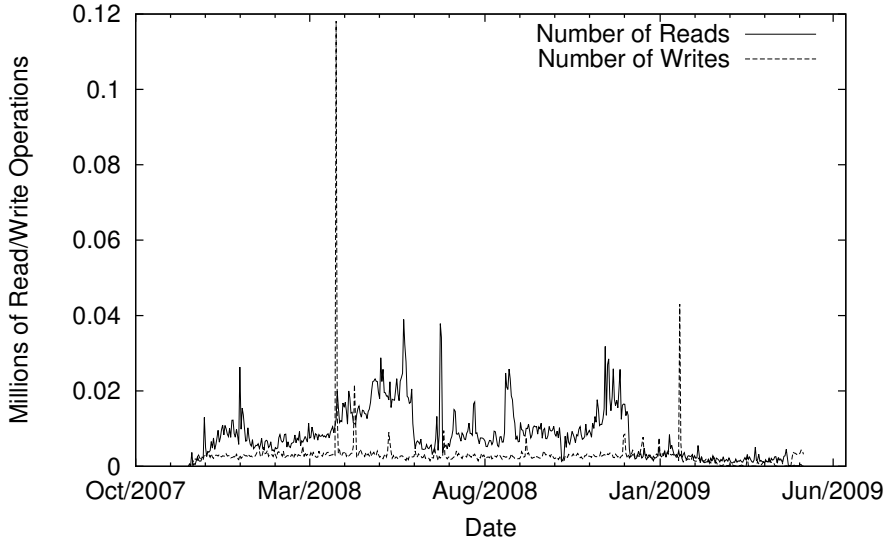


Figure 3.4: Read/write requests in the Internet Archive trace

storage providers gives a lower estimate of the monetary cost of switching storage providers.

3.3.2 Cost of moving to the cloud

We estimated the monetary cost of moving the Internet Archive data to the cloud according to published pricing schemes of the leading public cloud storage providers and the trace described in Section 3.3.1. Storage providers offer bracket-based pricing schemes depending on the amount of size of stored data, monthly bandwidth consumption for data transfers, and the total number of operations issued by customers [1, 9, 11, 13, 14].

In Figure 3.5, we model the cost of servicing the Internet Archive by using a single storage provider, the DuraCloud scheme of full replication to two providers (S3 USA and Azure), and RACS using three providers (S3 USA, S3 N. CA, and Azure)[1]. Storage providers compete, aggressively, on price. For exam-

[1] Amazon S3 is offered in multiple regions with different pricing per region [1].

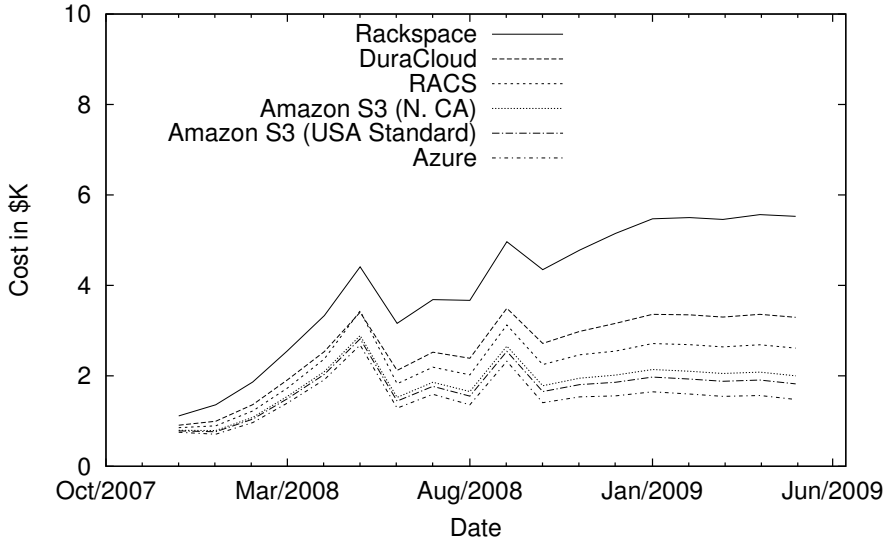
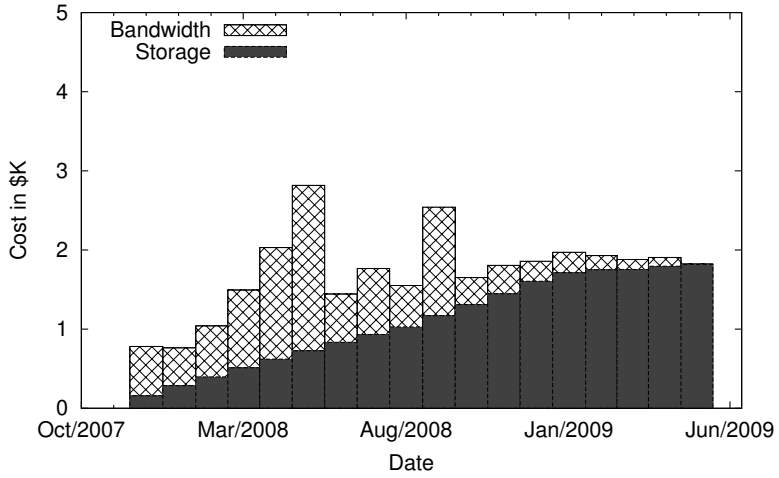


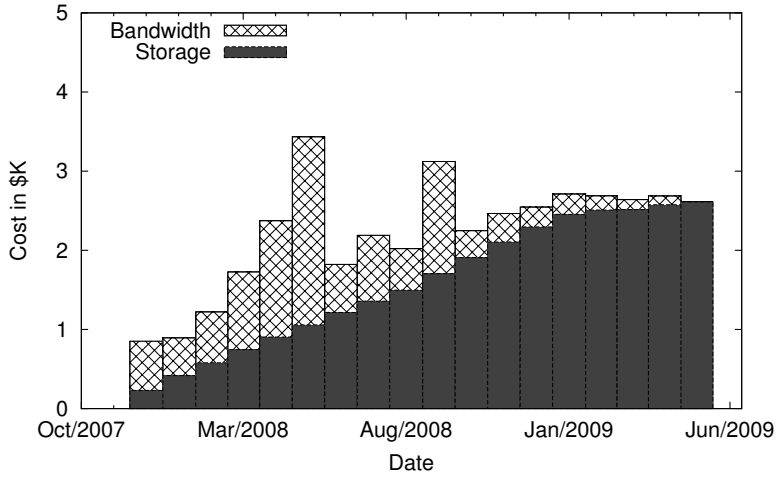
Figure 3.5: Estimated monthly costs of hosting on the cloud

ple, it is four times as expensive to host the Internet Archive's data on Rackspace than on Amazon S3 given today's prices. However, this has not always been the case; Rackspace and Amazon offered comparable prices when we first ran our study in 2010. This highlights the fluidity of the market, and the consumer need to quickly adapt to vendor price changes.

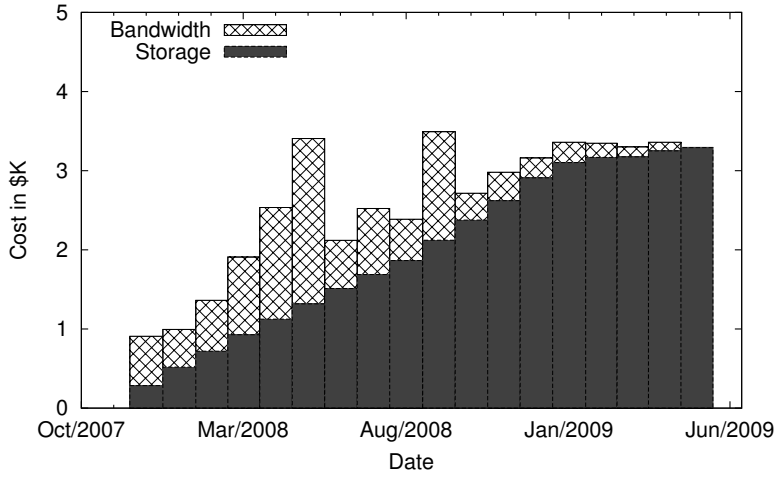
As expected, DuraCloud's approach of using full-replication doubles the hosting costs and is more expensive than using an erasure coding striping technique as with RACS. The added overhead cost of RACS depends on the erasure-code configuration, the more stripes result in lower overhead. Figure 3.6 shows the breakdown of the cloud storage cost in three configurations: A single provider, the DuraCloud system, and with RACS using 3 repositories. In all cases, the monthly bill is dominated by storage costs. This explains why a simple full replication scheme as proposed in DuraCloud is very costly. It also explains why striping cloud storage across a large number of providers so as to limit the overhead added to each individual provider's share is preferable.



(a) Hosted on Amazon S3, USA region



(b) Hosted with RACS(m=2,n=3) on S3 USA, S3 N. CA, and Azure



(c) Hosted with DuraCloud on S3 USA, and Azure

Figure 3.6: Breakdown of monthly cloud storage costs

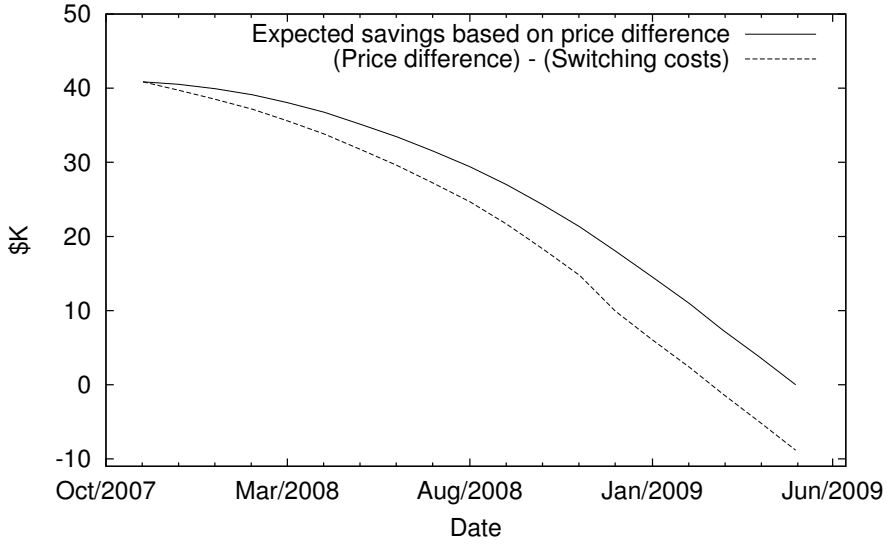


Figure 3.7: Month-by-month switching benefit (non-RACs solution)

3.3.3 Cost of vendor lock-in

To quantify the cost of vendor lock-in, we assumed that the Internet Archive is hosted on Rackspace and calculated the cost of migrating the data to Amazon S3 (USA region).

The solid line in Figure 3.7 shows total expected savings by the end of the trace period if the data was moved to the cheaper provider at different points in time. If the move happened at the beginning of the trace period, the total savings based purely on price differences would be more than $40K over the 18 month period. However, if we take into account the actual cost of moving the data from the old provider to the new provider–the cost of data transfer bandwidth out of the old provider, then the savings due to price differences quickly erode as shown by the dashed line. Indeed, by the end of the trace period, to the cheaper provider will be more costly than staying at the more expensive provider, simply due to the cost of transferring all the data that has accumulated at the old provider.

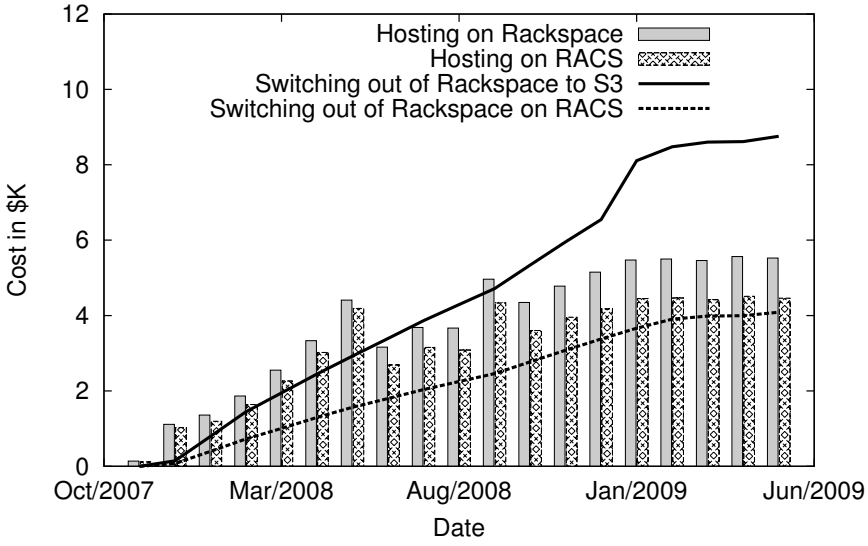


Figure 3.8: Month-by-month switching costs for various configurations

The cost of making the switch to the cheaper storage provider is shown in Figure 3.8 by the solid line. To put the cost in context, the monthly cost of hosting the data on the old provider (Rackspace) is also displayed. Even though the monthly cost of hosting the data never exceeds $6K, the cost of switching the entire dataset nearly reaches $9K. The longer an organization stays with a more expensive storage provider, the more costly it will be to switch to a new provider. Alternatively, by striping data across multiple providers, the cost of moving out any single provider is reduced. To highlight the difference, the costs of hosting the data using RACS (on Azure, S3 N. CA, and Rackspace), and then migrating the Rackspace portion to S3 USA are also shown in Figure 3.8.

3.3.4 Tolerating price hikes

Switching vendors is not the only recourse to storage provider price increases; RACS can serve read operations using redundant shares from cheaper providers, without immediately switching out of the expensive provider. As-

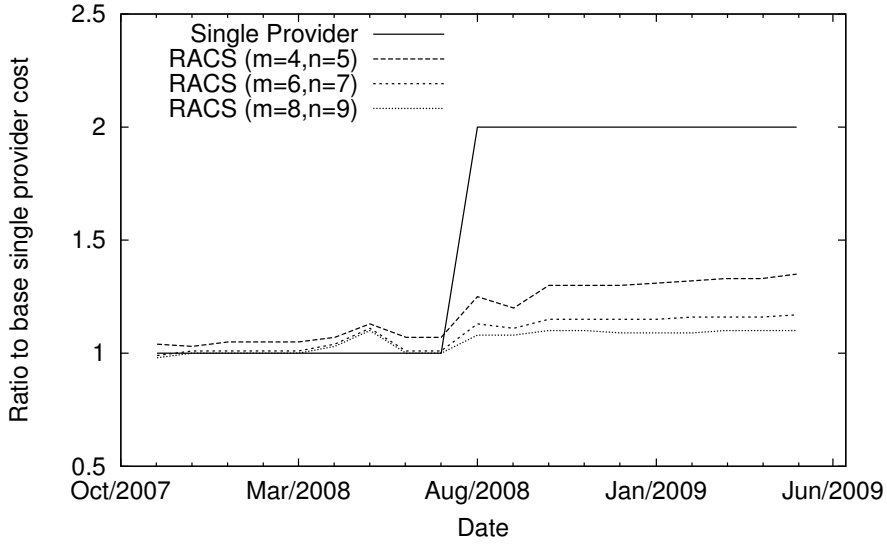


Figure 3.9: Tolerating a vendor price hike

sume that a single provider doubles its prices halfway through the trace, figure 3.9 shows the effects of the price increase on hosting with a single storage provider and with multiple RACS configurations. As expected, striping data across a larger number of providers results in the greatest dampening of the hike. Even an $(m = 4, n = 5)$ erasure-code, which is possible today, reduces the effects of a potential drastic price hike. Coupled with the low cost of switching vendors, as shown in Figure 3.8, clients can use RACS to ensure against potential mischievous behavior from storage providers. As a result, RACS gives more client control for switching providers, and protects clients from economic failures.

3.4 Prototype Evaluation

To evaluate our RACS prototype implementation, we ran several benchmarks with various (m, n) values to determine RACS's operational overhead. We also

tested RACS's response time against Rackspace to confirm that RACS does not introduce unacceptable latency.

3.4.1 Benchmarks

Our benchmarks use Cumulus [118] to back-up a user's home directory to the cloud. They were run using a single RACS proxy running on the client machine. All repositories were backed by Amazon S3 to obtain an apples-to-apples comparison between operation counts[2]. ZooKeeper was disabled, since there was only a single client. Note that, although S3 objects can be copied inside of S3 without incurring bandwidth charges, we did not do this—to move objects between repositories, we downloaded and re-uploaded them.

The benchmarks are as follows:

Upload snapshot. Cumulus stores backup snapshots on Amazon S3. Cumulus packs files into large segments to reduce the number of requests sent to S3, and it compresses segments before uploading them. Our experiment used Cumulus to take a snapshot of workstation home directories totaling about four gigabytes. After compression, the snapshot had 238 segments, ranging from four to six megabytes each, for a total of 1.2 gigabytes. Cumulus uploads each segment

Vendor Migration. With the backup snapshot already loaded into the cloud, we instruct the RACS server to migrate the entire contents of one repository to a new repository. This simulates leaving a vendor in the case of economic failure or new opportunity.

[2]In real-world usage, of course, using the same storage provider for every repository negates the purpose of RACS

	S3	RACS (2,3)	RACS (4,5)	RACS (5,7)
`put` and `list` requests	241	731	1209	1747
`get` requests	240	485	485	487
Data Transfer In (MB)	1199	1811	1486	1656
Data Transfer Out (MB)	20	34	34	28
One-time cost (USD)	$0.12	$0.19	$0.16	$0.18
Monthly cost (USD)	$0.18	$0.27	$0.22	$0.24
One-time cost relative to S3	1	1.55	1.33	1.5
Monthly cost relative to S3	1	1.51	1.24	1.38

Table 3.2: Upload snapshot benchmark
Cost of running the "upload snapshot" benchmark on S3 and on various RACS deployments using S3 as a storage provider.

Restore snapshot. Retrieves all segments for a particular snapshot from the cloud storage repository (i.e. use RACS to `get` each segment), then unpacks each segment locally into files to give a user a file system view of the snapshot.

For each run, we collect the metrics used to determine prices for Amazon S3 USA and estimate the cost of the trial.

Table 3.2 shows the relative cost of running RACS for a Cumulus backup as compared to a baseline running on S3. RACS issues more requests, but the cost of this benchmark is dominated by large uploads. There are no surprises; we expect RACS uploads to use a factor of n/m bandwidth and storage compared to the S3 baseline (i.e. an increase of $\frac{n-m}{m}$), and total cost reflects this in the bottom third of Table 3.2. The three RACS deployments have different prices, with $(m = 4, n = 5)$ being the cheapest. Obviously, it is desirable to bring n/m as close to one as possible. We did not collect data for incremental backup snapshots, but they should adhere to the same costs relative to the baseline as the full snapshot upload. One side-effect of RACS is improved bandwidth-saturation of a client

	S3	RACS (2,3)	RACS (4,5)	RACS (5,7)
`put` and `list` requests	4	4	4	4
`get` requests	243	482	972	1215
Data Transfer In (MB)	28	30	30	31
Data Transfer Out (MB)	1191	1235	1263	1210
Cost (USD)	$0.20	$0.21	$0.21	$0.21
Cost relative to S3	1	1.05	1.05	1.05

Table 3.3: Restore snapshot benchmark
Cost of running the "restore snapshot" benchmark on S3 and on various RACS deployments using S3 as a storage provider.

	S3	RACS (2,3)	RACS (4,5)	RACS (5,7)
`put` and `list` requests	247	247	247	247
`get` requests	243	241	243	243
Data Transfer In (MB)	1211	610	306	244
Data Transfer Out (MB)	1214	618	316	242
Cost (USD)	$0.32	$0.16	$0.09	$0.07
Cost relative to migrating all the data from S3	1	0.51	0.26	0.21

Table 3.4: Vendor migration benchmark
Cost of running the "migration snapshot" benchmark on S3 and on various RACS deployments using S3 as a storage provider. For RACS, all the data on a single repository was migrated to a different storage provider.

that issues serial `put` requests. We observed this with Cumulus, which had dips in network utilization between sending objects.

Table 3.3 gives the results of downloading the backup snapshot from the cloud. This consists almost exclusively of `get` requests, which we expect to consume roughly the same bandwidth as the baseline plus additional overhead due to the multiplicative increase in the number of requests. It is clear that RACS is more flexible for applications that favor `get` requests.

Table 3.4 confirms that RACS does reduce the cost of vendor migration, giving consumers greater mobility in the marketplace and more leverage with their providers. Because RACS breaks up data objects into shares of size $\frac{1}{m}$ and

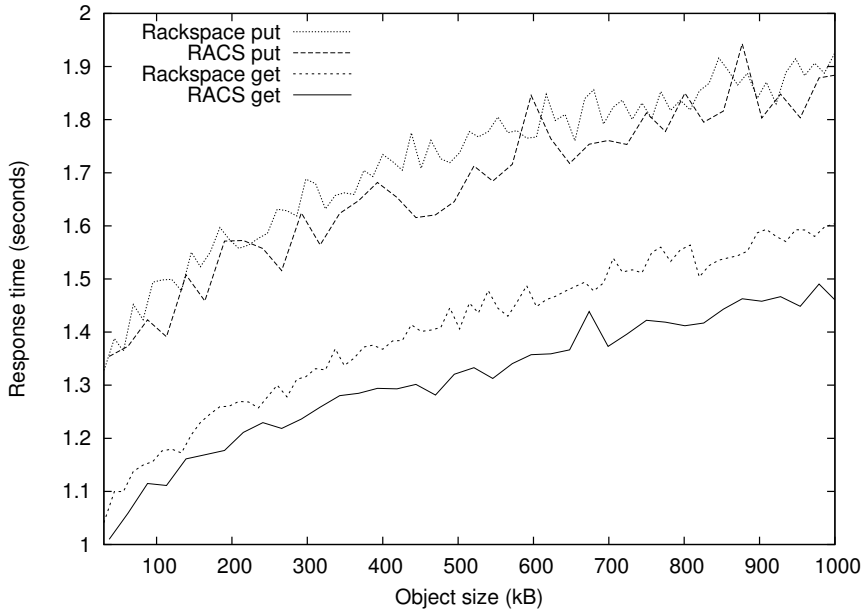


Figure 3.10: RACS vs. Rackspace `put` and `get` latencies

spreads these shares across providers, the cost of switching providers under RACS is roughly $\frac{1}{m}$ that of the baseline as the last line of Table 3.4 shows. Note that the number of requests is not increased because RACS is simply copying data from one repository to another.

3.4.2 Performance

Figure 3.10 compares the responsiveness of RACS to directly connecting to Rackspace. For this experiment, RACS was using a (2,3) configuration, backed by three Rackspace repositories. RACS and the client were executed on the same machine at Cornell. We ran RACS at four different periods during the day, to filter out any transient network conditions. In each period, the benchmark was run 10 times. The reported results are averages of all runs, and the standard deviation was too small to plot. RACS does not lag behind. We attribute this to

parallelism: Even though RACS is uploading 50% more data for `put` requests after erasure coding, it saves time by running repository queries concurrently.

RACS' major CPU expense is erasure coding. The prototype uses the Zfec [90] Reed-Solomon erasure coding library. On 2 GHz Core 2 Duo machine, we clocked Zfec encoding at a rate of 95 MB/sec, and decoding 151 MB/sec, using only one CPU core. We conclude that erasure coding is not likely to become a bottleneck until gigabit ethernet speeds are involved. Our RACS proxy's CPU usage hovered at around 25% during the benchmarks. Beyond these speeds, Distributed RACS can be used to scale beyond the limitations of one proxy. Alternately, we might choose to use more efficient erasure codes, such as those used by RAID 6, to increase erasure coding throughput—albeit at a loss of configurable (m, n) parameters.

Distributed RACS has been tested with two concurrent RACS proxies sharing a single remote ZooKeeper server. The extra overhead was negligible, except when contention forced requests to the same key to be serialized. The contention overhead could be reduced by using an even finer-grained locking system able to control access to individual repositories while guaranteeing external consistency, although the potential for long waits and serialized access is fundamental. RACS could also hypothetically buffer waiting events on the proxy and return immediately to the client, giving the client an illusion of not needing to wait, at the risk of data loss if the RACS proxy crashes.

CHAPTER 4

LEVERAGING SHARDING IN THE DESIGN OF SCALABLE REPLICATION PROTOCOLS

In this chapter we discuss replication in datacenter services underpinning cloud storage services, from the previous chapter, and other client-facing cloud computing services. Datacenter services are usually made scalable by partitioning data into independent shards, each then replicated for enhanced availability and failure tolerance. But with replication comes the question of consistency. A *strongly consistent* replicated system behaves, logically, identical to its unreplicated counterpart. However, many large-scale fault-tolerant services used in datacenters today provide weaker consistency guarantees, such as eventual [27,117] or causal [79] consistency. These weaker guarantees are easy scale-out and offer predictable performance in the face of crash failures or overload. Although relaxed consistency is useful in many contexts, programming against weakly consistent services is difficult [108]. As such, there has been a resurgence in large scale strongly consistent services, such as Spanner, Megastore, Scatter, and HyperDex [28,49,58,63].

A challenge brought on by scale is configuration management. Node reconfiguration in strongly consistent services usually relies on having an *external* replicated and failure-tolerant centralized configuration management service (CCM), such as Chubby and ZooKeeper [41, 69]. Internally, most CCMs use a state machine replication protocol, such as Paxos or Zab [75,96].

In this chapter, we present an *elastic replication* protocol that leverages the sharded nature of modern datacenter services to support flexible reconfiguration without compromising strong consistency semantics or relying on CCMs. At a high level, each shard in elastic replication serves a dual purpose: It stores

application state, and it manages the configuration of another shard. A shard's configuration is separated from its state, and a shard can only be reconfigured when instructed by another shard. This independence of state and configuration eliminates the need for solving consensus to reconfigure the service, as compared with using an external configuration master, such as in Vertical Paxos [76] or other existing systems.

Shards are organized into monitoring/reconfiguration rings called *elastic bands*. Each shard belongs to one ring and monitors the successor shard on the ring. For liveness, elastic replication makes the following minimal assumptions:

(A0) Each faulty replica is eventually suspected.

(A1) Each shard has at least one non-faulty replica.

(A2) At any time there is at least one shard in which no replicas are suspected of being faulty.

If these assumptions are violated, the system might lose data or require external intervention to reconfigure.

Elastic replication offers the following benefits, which we demonstrate throughout the chapter:

- **Minimal cost of replication.** In order to survive f simultaneous failures, a shard requires only $f + 1$ replicas. Additionally, message and computational overheads are low.
- **No dependency on accurate failure detection.** Setting the right values for ping intervals is notoriously difficulty — choosing an incorrect value could lead to false positives and incorrect system behavior [106]. As such, the safety of our protocol does not depend on accurate detection of failures or the value of ping intervals.

- **Simple reconfiguration.** Reconfiguration does not violate consistency guarantees [103], and is both fast and straightforward.
- **Customizable consistency.** Strong consistency guarantees such as linearizability [68] are provided to applications that need them, while other applications receive improved timeliness, particularly in the face of network partitioning, in exchange for weaker guarantees [52, 94, 117, 123].

4.1 Elastic Replication

In this section, we specify, refine, and compare elastic replication to other replication protocols. We develop elastic replication in steps. First, we show how a single shard can be replicated given a sequence of configurations that is defined *a priori*. Next, we show how collections of shards can manage configurations of one another. Our discussion starts with a high-level specification which is then refined. Section 4.1.7 describes an actual implementation of elastic replication.

4.1.1 Environment model

An asynchronous environment is assumed with no bounds on processing times or message delays. Faulty replicas cannot be distinguished from slow ones. Failures are assumed to be either crash or omission failures (although the method can be generalized to Byzantine failures as well [115]). Communication channels are assumed to be reliable and deliver messages in FIFO order.

specification `Shard`:
  var $\mathcal{I}, \mathcal{O}, \mathcal{H}$
  initially: $\mathcal{I} = \phi, \mathcal{O} = [\,], \mathcal{H} = [\,]$

  transition `invoke`(o):
    precondition: $o \notin \mathcal{I}$
    action: $\mathcal{I} := \mathcal{I} \cup \{o\}$

  transition `apply`(o):
    precondition: $o \in \mathcal{I} \wedge o \notin \mathcal{H}$
    action:
      $\mathcal{H} := \mathcal{H} :: o$

  transition `respond`(o):
    precondition:
      $o \in \mathcal{H} \wedge$
      $(\mathit{pref}(\mathcal{H}, o') \in \mathcal{O}\ \forall o' \in \mathcal{H} \mid o' \prec o)$
    action:
      $\mathcal{O} := \mathcal{O} :: [\mathcal{H} :: o]$

Figure 4.1: Shard specification
Notation:
$\mathit{pref}(\mathcal{H}, o')$ is a prefix of $\mathcal{H}$ ending with o'.
$o' \prec o$ denotes that o' appear before o in $\mathcal{H}$.
$[\,]$ denotes an empty sequence.

4.1.2 Replicating single shards

Figure 4.1 shows a high-level specification of a shard in our system. We model the state of a shard as two variables that are both initially empty:

- $\mathcal{I}$ is a set of invoked operations.
- $\mathcal{H} = o_1 :: o_2 :: o_3 :: ...$ is a finite history (sequence) of operations.
- $\mathcal{O} = \mathcal{S}_1 :: \mathcal{S}_2 :: \mathcal{S}_3 ...$ is a sequence of outputs. Each element $\mathcal{S}_i$ is a sequence of operations such that $\mathcal{S}_i$ is a prefix of all $\mathcal{S}_j$ in $\mathcal{O}$ where $i < j$.

Three transitions are supported:

- `invoke`(o): is a transition whereby an operation, o, is added to the set of invoked operations.
- `apply`(o): is a transition whereby an invoked operation, o, not already in the shard's history, is appended to the history.
- `respond`(o): is a transition whereby a sequence $\mathcal{S}_i$ (that is a prefix of $\mathcal{H}$ ending with operation o) is appended to $\mathcal{O}$ on the condition that all prefixes of $\mathcal{S}_i$ are already in $\mathcal{O}$.

The shard specification has the following two safety properties:

- *Persistence:* once an operation is added to the shard history, it is never removed. Clients are also exposed to this property through outputs in $\mathcal{O}$. For all $\mathcal{S}_i, \mathcal{S}_j \in \mathcal{O}$ where $i < j$, it is the case that $\mathcal{S}_i$ is a prefix of $\mathcal{S}_j$.
- *Linearizable consistency:* every operation is applied atomically between the time of invocation and response.

Additionally, the liveness property we are interested in is:

- *Termination:* for every invoked operation, o, there will eventually be a sequence, ending in o, added to $\mathcal{O}$. Simply put, every invocation will eventually get a response.

To make the shard highly available, we use replication and dynamically change the configuration of replicas in order to deal with crash failures and unresponsiveness. For now, assume the existence of an unbounded sequence of configurations $\mathcal{C} = C_1 :: C_2 :: C_3 :: ....$ The boolean function *succ*(C, C') evaluates to `true` if and only if C' directly follows C in $\mathcal{C}$. Each configuration C_i consists of the following:

- C_i.*replicas*: a set of replicas; and

- C_i.*orderer*: a designated replica in C_i.*replicas*.

For simplicity, we initially assume that the replicas of any two configurations are disjoint. Later, we drop this impractical assumption. Replicas in the same configuration are called *peers*. In order to tolerate up to f failures, each configuration needs at least $f + 1$ independent replicas. A replica r has the following state:

- r.*conf*: the configuration this replica belongs to;
- r.*orderer*: the orderer of this configuration;
- r.*mode*: is either `PENDING`, `ACTIVE`, or `IMMUTABLE`. Initially all replicas in C_1 are `ACTIVE`, while replicas in other configurations are all `PENDING`;
- r.*history*: a sequence of operations $o_1 :: o_2 :: ....$ In practice, replicas maintain a state produced by this history, but this model is easier to understand. The history of `PENDING` replicas is empty;
- r.*stable*: the length of a prefix of the history that r knows to be *persistent*; i.e., operations that appear in the history now and forever after. Initially, r.*stable* is 0, and the inequality $0 \leq r.\textit{stable} \leq \textit{length}(r.\textit{history})$ always holds;
- r.*ops*: a set of operations. Initially empty.
- r.*invocations*: a set of operations that r knows to have been invoked by a client and are either in r's history, or are intended be added to it. Note that r.*history* is an ordered sequence while r.*invocations* is an unordered set. r.*invocations* is initially empty.
- r.*outputs*: a sequence of outputs, each of which is a sequence of operations, that have been produced by the replica. r.*outputs* is thus a sequence of sequences, and it is initially empty.

Let $gcp_h(C)$ be the greatest common prefix of the histories of the replicas of configuration C. Also, $\bigcap_{ops}(C)$ is the intersection of all the *ops* sets of the different replicas of C. Finally, *prefix*$(r.history, i)$ is a prefix of length i of the sequence $r.history$.

Figure 4.2 shows five atomic transitions that are allowed:

1. `addOp`(r, o): if r is an active orderer of a configuration, it is allowed to add an operation o to its set of operations;
2. `adoptState`(r): a non-`IMMUTABLE` replica r may adopt the state of the orderer in its configuration as long as the orderer has a stable prefix that is at least as long as that of the replica;
3. `learnPersistence`(r, s): an active replica r may extend its set of invoked operations to include the intersection of all operations (*ops*) at all replicas in its configuration. If r is the orderer, it also extends its history with invoked operations that are not in its history yet. The replica additionally extends its stable prefix up to the greatest common prefix of all histories of its peers, and includes all prefixes of its history, up to the stable prefix, into the set of outputs;
4. `wedgeState`(r): an active replica r may cease operation, allowing the next configuration to make progress;
5. `inheritHistory`(r, r'): a pending replica r may assume the *ops*, invocations, history, outputs, and stable prefix of an `IMMUTABLE` replica r' in the prior configuration and become active.

The transitions specify what actions are safe (ensure persistence), but not when or in what order to do them. We now sketch in a more operational manner when non-faulty replicas perform transitions in the specification above.

specification `Replicas`:
  transition `addOp`(r, o):
    precondition:
      $r.mode = \texttt{ACTIVE} \wedge r = r.orderer$
    action:
      $r.ops := r.ops \cup \{o\}$
  transition `adoptState`(r):
    precondition:
      $r.mode \neq \texttt{IMMUTABLE} \wedge r.orderer.mode \neq \texttt{PENDING} \wedge$
      $r.history \neq r.orderer.history \wedge r.stable \leq r.orderer.stable$
    action:
      $r.ops := r.orderer.ops$
      $r.invocations := r.orderer.invocations$
      $r.history := r.orderer.history$
      $r.output := r.orderer.output$
      $r.stable := r.orderer.stable$
  transition `learnPersistence`(r, s):
    precondition:
      $r.mode = \texttt{ACTIVE}$
    action:
      $r.invocations := \bigcap_{ops}(r.conf)$
      if $r = r.orderer$**:**
        $r.history := r.history :: [r.invocations \backslash r.history]$
      if $r.stable < s \leq gcp_h(r.conf)$**:**
        $r.stable := s$
        for $i = r.stable$ **to** s**:**
          $r.output := r.output :: prefix(r.history, i)$
  transition `wedgeState`(r):
    precondition:
      $r.mode = \texttt{ACTIVE}$
    action:
      $r.mode := \texttt{IMMUTABLE}$
  transition `inheritHistory`(r, r'):
    precondition:
      $r.mode = \texttt{PENDING} \wedge succ(r'.conf, r.conf) \wedge r'.mode = \texttt{IMMUTABLE}$
    action:
      $r.mode := \texttt{ACTIVE}$
      $r.ops := r'.ops$
      $r.invocations := r'.invocations$
      $r.history := r'.history$
      $r.output := r'.output$
      $r.stable := r'.stable$

Figure 4.2: Specification of elastic replicas

Clients send operations to an active orderer, which will add each received operation to its set of operations (possibly filtering out duplicates). This corresponds to the `addOp` transition. Note that we are not ruling out that there might exist multiple active orderers of different configurations. However, as we will prove in Section 4.1.3, only one configuration at a time will be composed of all active replicas.

The goal of an active orderer is to get its peers to accept its history. Upon becoming active, and upon adding operations to its set of operations, the orderer notifies its peers. Corresponding to the `adoptState` transition, a non-`IMMUTABLE` replica will adopt the set of operations, invocations, history, and output of the orderer if the orderer has a stable prefix that is at least as long as its own stable prefix—it is an invariant that replicas never truncate their stable prefix. Note that our specification does not say how operations are distributed, providing flexibility to the implementation.

As soon as an operation is in the set of operations (*ops*) of all peers of a configuration, it is *invoked*. The orderer extends its history with invoked operations not currently in its history via the `learnPersistence` transition. Other replicas eventually learn about the extended history via the `adoptState` transition. Note that because $r.invoked$ is a set, there is no order between invoked operations. Thus when an active orderer extends its history with invoked operations, it may choose to order them however it wants at the end of its history.

Once an operation is in the history of all replicas, it is persistent. Replicas can only act upon an operation once they learn it is persistent. The way this could be done is as follows: After receiving a request to adopt the history of the orderer, the replica returns the length of the common prefix of its history with that of the orderer. If an orderer receives a response from all its peers, it can calculate

the minimum and increase its stable prefix accordingly (corresponding to the `learnPersistence` transition). The orderer would then notify its peers, who can then update their stable prefix as well (also `learnPersistence`). When a replica updates its stable prefix, it extends its sequence of outputs with all prefixes of its history from the old stable prefix to the new one via `learnPersistence`.

If an active replica, ρ, suspects that one of its peers is faulty, ρ goes into `IMMUTABLE` mode (`wedgeState` transition). Once `IMMUTABLE`, the state of a replica r can no longer change and only operations already in $r.history$ can become persistent in its configuration. Replicas in the subsequent configuration can transition from pending to active mode using the history of an `IMMUTABLE` replica (the `inheritHistory` transition), as described below, and continue to make progress.

4.1.3 Safety and refinement mapping

We now show that the `Replicas` specification refines the high-level `Shard` specification. The collective states of the replicas maps to the state of the shard as follows:

- $\mathcal{I} = \max_{C \in \mathcal{C}} \bigcap_{invoked}(C)$.
- $\mathcal{H} = \max_{C \in \mathcal{C}} gcp_h(C)$.
- $\mathcal{O} = \max_{C \in \mathcal{C}} gcp_o(C)$.

That is, $\mathcal{I}$ is the largest set of invoked operations shared by all replicas of a configuration. Additionally, $gcp_o(C)$ is the greatest common prefix of the $r.output$ sequences of all replicas in configuration C.

The following invariants are easily proven:

- For any replica r, $gcp_h(r.conf)$ is a prefix of $r.history$;
- If a configuration C contains a `PENDING` replica, then $gcp_h(C)$ is empty;
- Replicas cannot truncate their stable prefix;
- For any configuration that has an `ACTIVE` or `IMMUTABLE` replica, all the predecessor configurations have at least one `IMMUTABLE` replica.

Unlike other replication protocols such as Primary-Backup, Chain Replication, or State Machine Replication, it is *not* an invariant that, given two histories of two different replicas in a configuration, one is a prefix of the other. This is because there is no order defined on how invoked operations are appended to an active orderer's history. However, it is the case that the stable prefix of any replica is always a prefix of the histories of the other replicas. To illustrate, consider a configuration C_1 consisting of replicas $\{r_1, r_2, r_3\}$, where r_1 is the orderer, all replicas are `ACTIVE`, the history at all the replicas is $\mathcal{H}$, and operations $\{o', o''\}$ are invoked but not added to the history yet. Also let configuration C_2 be the successor of C_1, with C_2 being composed of `PENDING` replicas $\{r_4, r_5\}$, and r_4 being the orderer. Let transition r_1 extend its history with $[o' :: o'']$ followed by transition `adoptState`(r_2). At this point, $r_1.history = [\mathcal{H} :: o' :: o'']$, $r_2.history = [\mathcal{H} :: o' :: o'']$, and $r_3.history = \mathcal{H}$. Next, let transitions `wedgeState`(r_2) and `wedgeState`(r_3) take place, followed by `inheritHistory`(r_4, r_3), then `inheritHistory`(r_5, r_2), then r_4 extends its history with $[o'' :: o']$. At this point, $r_4.history = [\mathcal{H} :: o'' :: o']$, $r_5.history = [\mathcal{H} :: o' :: o'']$, and neither of them is a prefix of the other.

An important invariant that holds over the states of replicas is the following:

Stable Prefix Invariant: The stable prefix of a replica's history is a prefix of the history of each of its non-`PENDING` peers.

Proof. Initially, all histories are empty, so the invariant holds in the initial state. We will now show that each transition maintains the invariant.

1. `addOp`(r, o): This transition does not change the stable prefix of any replica;
2. `adoptState`(r): This transition copies the history and stable prefix from the orderer. The orderer's stable prefix satisfies the invariant, and thus the transition maintains the invariant;
3. `learnPersistence`(r, s): This transition, as a precondition, requires that s corresponds to a prefix of all histories of the peers, and thus evidently enforces the invariant for the state after the transition;
4. `wedgeState`(r): This transition does not change the stable prefix of any replica;
5. `inheritHistory`(r, r'): This transition can only happen to replicas that are in `PENDING` mode. Let $C = r.conf$ and $C' = r'.conf$. Observe that the `learnPersistence` transition can only happen in a configuration that has no `PENDING` replicas, as the history of a `PENDING` replica is empty. Thus we know that the `learnPersistence` transition cannot have occurred at replicas of C. Also note that the initial configuration has no `PENDING` replicas, and thus C is not the initial configuration.

   All non-`PENDING` replicas must thus have obtained their history from an `IMMUTABLE` replica in C' (`inheritHistory` transition) or from the orderer of C (`adoptState` transition). As the `addOp` transition does not affect the invariant, we will for simplicity of exposition assume that no operations have arrived at the orderer. Because the orderer must have obtained its history from an `IMMUTABLE` replica of C' *all* histories at non-`PENDING` replicas are from `IMMUTABLE` replicas in C'. Since the invariant

holds in C', and since the histories of `PENDING` replicas are empty, the invariant must also hold in C after this transition.

As none of the possible transitions result in a state that violate the property, the property is invariant. ■

Lemma 1. *For any configuration C and any non-*`PENDING` *replica r in the successor configuration of C, there exists an* `IMMUTABLE` *replica in C whose history is a prefix of r.history.*

Proof. If r is the orderer, then its history must have first been inherited from an `IMMUTABLE` replica in C, and then possibly extended with new operations (using `learnPersistence` transitions). Because no transition can truncate the history of the orderer, the lemma holds. If r is not the orderer, then its history was either directly inherited from an `IMMUTABLE` replica in C, or it was adopted from the orderer. In either case, the lemma holds. ■

Corollary 2. *For any configuration C and any non-*`PENDING` *replica r in the successor configuration of C, $gcp_h(C)$ is a prefix of r.history.*

Corollary 3. *For any two configurations C and C', C before C' in $\mathcal{C}$, and r a non-*`PENDING` *replica of C', $gcp_h(C)$ is a prefix of r.history.*

Lemma 4. *For any two configurations C and C', either $gcp_h(C)$ is a prefix of C' or vice versa.*

Proof. Note that if either C or C' contains `PENDING` replicas, then its gcp_h is empty and the lemma holds trivially. If neither contains `PENDING` replicas, then the lemma follows from the corollary above. ■

Similar arguments are followed for $gcp_o(C)$, and $\bigcap_{invoked}(C)$.

Theorem 5. *Specification* `Replicas` *refines specification* `Shard`.

Proof. By induction on the number of transitions. For the initial state, all replica's invocations, histories, and outputs are empty and thus map to the empty shard invocations $\mathcal{I}$, history $\mathcal{H}$, and outputs $\mathcal{O}$. We now show that each `Replicas` transition corresponds to a transition in `Shard` or leaves the state of `Shard` unchanged (a so-called *stutter*). A transition at a replica r in configuration C may change $gcp_h(C)$, but cannot cause an inconsistency in $\max_{C \in \mathcal{C}} gcp_h(C)$ because of Lemma 4. Examining each transition:

1. `addOp`(r, o): This transition only modifies an internal variable and does not affect invocations, histories, or outputs. Therefore, it is a stutter;
2. `adoptState`(r): Because r adopts the invocations, history, and outputs of another replica, it cannot cause the greatest common prefixes (or the intersection of invokes) to be truncated. If the transition causes $\bigcap_{invoked}(r.conf)$ to be expanded by o, then the transition corresponds to `invoke`(o). If the transition causes $gcp_h(r.conf)$ to be extended by o then the transition corresponds to `apply`(o). If the transition causes $gcp_o(r.conf)$ to be extended by a prefix of the history ending with o, then the transition corresponds to `respond`(o). Otherwise the transition is a stutter;
3. `learnPersistence`(r, s): If the transition causes $\bigcap_{invoked}(r.conf)$ to be expanded with o, then the transition corresponds to `invoke`(o). If the transition causes $gcp_h(r.conf)$ to be extended by o, then the transition corresponds to `apply`(o). If the transition causes $gcp_o(r.conf)$ to be extended by a prefix of the history ending with o, then the transition corresponds to `respond`(o). Otherwise the transition is a stutter;
4. `wedgeState`(r): This transition does not affect any invokes, histories, or outputs. Therefore it is a stutter;

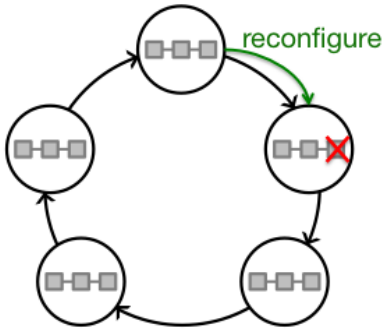


Figure 4.3: Illustration of an elastic band

Example of an elastic band. Each (replicated) shard is sequenced by its predecessor on the band as indicated by the arrows. The sequencer of a shard issues new configurations when needed.

5. `inheritHistory`(r, r'): r starts out with an empty history, and thus the transition cannot cause the greatest common invokes, histories, or outputs to be truncated. If the transition causes $\bigcap_{invoked}(r.conf)$ to be expanded with o, then the transition corresponds to `invoke`(o). If the transition causes $gcp_h(r.conf)$ to be extended by o, then the transition corresponds to `apply`(o). If the transition causes $gcp_o(r.conf)$ to be extended by a prefix of the history ending with o, then the transition corresponds to `respond`(o). Otherwise the transition is a stutter. ■

4.1.4 Elastic bands

Thus far we have assumed a single replicated shard, and an unbounded sequence of configurations that has been determined *a priori*. We now drop these assumptions and instead assume a dynamic set $\mathcal{X}$ of shards. Logically, each shard $x \in \mathcal{X}$ has a *sequencer* that determines its sequence of configurations. A sequencer can be further subdivided into two distinct functions: *sequencing mechanism* and *policy*.

The sequencing mechanism ensures that for every shard there is a non-branching history of configurations. The policy function determines when a configuration needs to be changed and what the new configuration should be. In this section, we focus only on the sequencing mechanism as discussion of policies is beyond the scope of this document.

In elastic replication, the sequence of configurations of a shard x is established by *another shard* x'. Shards are organized into one or more circular *elastic bands*, with the configuration of any shard x on a band being sequenced by exactly one other shard x' on the same band; its predecessor shard in the band. An elastic band is composed of at least two shards—because a single shard with a wedged replica cannot reconfigure itself alone. Since a shard can have only one sequencer, we conclude that a shard cannot be on two different bands at once. Figure 4.3 depicts an elastic band.

Each shard has dual responsibilities: to store and manipulate the application-specific state of its replicated state machine, and to issue new configurations for its successor shard in the band when needed—e.g. in response to failure.

We will now describe the shard sequencing-interface. Let $x.id$ be a unique identifier for shard x. The sequencing interface is accessible even when a replica is wedged and it consists of two operations:

- $s.storeConf(x.id, config)$: This makes s the sequencer of shard x, and makes *config* the configuration of x;
- $s.removeConf(x.id)$: If shard s has the configuration of x, it will stop being the sequencer for x and return the configuration of x. Otherwise, s will return an error.

A configuration itself consists of a tuple $\langle$*id*, *index*, *locations*, *orderer*$\rangle$. Here *id* is the shard identifier, *index* is the index in its sequence of configurations, *locations* is a set of host identifiers (e.g. TCP/IP addresses), and *orderer* is the host in *locations* that runs the orderer replica.

It is easy to insert into and remove shards from a band. Doing so would be under the control of a configuration management agent m, itself an object in a shard. Consider shards x and x' on a band, with x the sequencer of x'. To insert a shard y in between x and x', m first obtains the configuration of x' from x using *removeConf*, and then stores the configuration into y using *storeConf*, making y the configuration sequencer for x'. Then m stores the configuration of y into x using *storeConf*, making x the configuration sequencer for y. This concludes inserting a new shard into the band. Note that even though shard y is the new sequencer of x', shard x' does not need to be notified of the change since sequencing is a one-way relationship. Additionally, note that m *can* only do this if it has the configuration of y, and *should* only do this if y does not have a sequencer already.

To remove y, m first wedges y and removes the configuration of x' from y, and then stores this configuration into x, making x the sequencer of x'. Finally, m can get the configuration of y from x, and destroy y or put its configuration at a new sequencer.

4.1.5 Liveness

As mentioned in Section 4.1.2, the liveness property of interest to us here is *termination*—i.e., every invocation will eventually get a response. Elastic replication makes the following assumptions:

(A0) Each faulty replica is eventually suspected.

(A1) For any band, each shard contains at least one correct replica.

(A2) Each band always has at least one shard that has no replicas suspected of being faulty.

(A0) is just the *completeness* property of failure detectors [42]. If an active replica, ρ, suspects that one of its peers is faulty, ρ becomes `IMMUTABLE` (and keeps suspecting the peer). For this transition to occur, we need to assume that correct replicas eventually suspect faulty peers. The actual mechanism can be implemented with a simple pinging protocol; aggressive timeouts can be used to detect failures quickly without jeopardizing the safety guarantees given that the protocol does not assume anything beyond failure detectors in the $\diamond\mathcal{W}$ class [42].

(A1) is a standard assumption made by all replication protocols, and it is satisfied by having $f + 1$ replicas per shard if f replicas can fail simultaneously. If a shard in an elastic band does not meet (A1), then the history maintained by its replicas will be lost, thus compromising persistence. Additionally, invoked-but-not-yet-applied operations maintained by that shard will be lost and never applied, thus compromising liveness/termination.

(A2) is required because shards are reconfigured by other shards on the same band rather than by an external centralized configuration management service (CCM). A replica that suspects one of its peer replicas in its shard of being faulty wedges itself. Thus, shards with at least one failure suspicion cannot extend their stable history, and they cannot reconfigure their successor shards. As a result, if every shard in a band does has at least one suspected-faulty replica, operations that have been invoked but not applied yet will never be applied, thus violating the termination property. In systems where shards are reconfigured by a CCM, (A2) is replaced by an assumption:

specification Replicas++:
  transition inheritHistory2(r, C):
    precondition:
      $r.mode \neq$ PENDING $\wedge$ $succ(r.conf, C) \wedge$
      $r \in C.replicas$
    action:
      $r.mode :=$ ACTIVE
      $r.conf := C$
  transition inheritHistory3(r, r'):
    precondition:
      $r.mode =$ PENDING $\wedge$ $r'.conf = r.conf \wedge$
      $r'.mode \neq$ PENDING
    action:
      $r.mode :=$ ACTIVE
      $r.history := r'.history$
      $r.stable := r'.stable$

Figure 4.4: Additional *Replica* transitions

(A3) The centralized configuration manager does not fail.

In Section 4.2.1 we will provide an exact formulation of the probability that (A1) and (A2) are met, compare that to the probability that (A3) is met, and show that organizing shards into elastic bands can result in higher reliability compared to using a CCM.

4.1.6 Practical considerations

We have thus far assumed that successive configurations do not overlap—i.e., they have no replicas in common. We now drop this impractical assumption by adding two more transitions (Figure 4.4) to the specification Replicas (Figure 4.2).

Transition inheritHistory2(r, C) allows a replica that is not pending to move from configuration $r.conf$ to successor configuration C. It inherits its own history, and does not become IMMUTABLE. This, however, presents a problem,

since other replicas in C may now not have an `IMMUTABLE` replica in the previous configuration to inherit state from. The extended specification solves this problem by allowing pending replicas to inherit state from non-pending peers in the same configuration (transition `inheritHistory3`(r, r')).

Another impractical simplification made for ease of specification was that replicas maintain the entire history of operations. However, instead of the stable part of the history, replicas can maintain a *running* state. This is possible, because the stable part of the history is persistent and never is reversed. Replicas will need to queue the remaining operations until they are known to be stable or maintain a running state with a log of "undo" operations in order to be able to roll back. The latter would make it possible for applications to support weakly consistent semantics, where updates are exposed quickly but are not known to be persistent.

4.1.7 Implementation

As mentioned in Section 4.1.2, our specification does not describe how operations are distributed to replicas. In our implementation, we organized replicas within a shard in a chain akin to chain replication [116](CR). We chose this construction due to the simplicity of CR and its high-throughput properties.

The orderer is the head of the chain, and it sends operations along the chain. Each replica on the chain adds the operations to its history. When the tail replica adds an operation to its history, all replicas have the operations in their histories and thus the operation is persistent. This allows the tail to respond to the client. The tail then sends an acknowledgment along the chain in the other direction, so that other replicas can also learn that the operation is persistent and apply the operation to their state.

While similar, there are some important differences between elastic replication (ER) and the original CR:

- in ER, when a replica is unresponsive, a new chain is configured, possibly with a new collection of replicas. In CR, faulty replicas are removed from a chain and new replicas added to the end of the chain. The reason behind this difference is that CR assumes a fail-stop model [104] in which failures are detected accurately, whereas ER assumes that crashes cannot be detected accurately—a weaker assumption;
- in ER, read-only operations must be ordered, just like other updates, whereas in CR clients read directly from the tail. Again, this difference is because of the weaker failure detection assumptions made for ER: If the tail were incorrectly suspected of failure and the chain reconfigured, then the tail's state would become stale without it knowing that its configuration is no longer current. In ER, an old configuration is wedged and even read operations cannot be serviced. This apparent inefficiency of ER can be addressed by using *leases* [64] to obtain the same read efficiency as CR.

There are some subtle issues to consider when a chain is reconfigured, because each chain must satisfy the CR invariant that a server earlier in a chain has a longer history than a server that appears later [116]. ER thus ensures that when a chain is reconfigured, the replicas that were in the old configuration appear early in the new chain *in the same order as in the old configuration*, while new replicas appear at the end of the chain with an initially empty history.

Our shard implementation is similar to CRC Shuttle implementation of Byzantine CR. However, Byzantine CR relies on an external configuration master, while ER delegates reconfiguration to other shards on the elastic band.

For increased efficiency, we can exploit parallel access and allow clients to read from any replica, but the result is weaker semantics. If clients read the stable running state of any replica, then they know the state is persistent, but possibly stale. If clients read the full history of any replica, then they are not guaranteed that the state is persistent or that the order of operations stays the same. It is for the application programmer to know whether such weaker semantics are acceptable.

4.1.8 Reconfiguration discussion

Reconfiguration prompts several natural questions: How is a new shard configuration chosen? How is the new replica membership decided? How is the next configuration orderer selected? These concerns are matters of *policy*. Elastic replication separates mechanism from policy [30] and is only focused on mechanism. Thus, any configuration with any set of replicas and any orderer could be chosen to reconfigure an existing shard without compromising correctness. In fact, the sequencing shard could be reading a predetermined list of configurations off a disk and it would not affect system safety.

In our implementation of elastic replication, when a replica is being unresponsive, we restore service by wedging the replica's current configuration and issuing a new configuration. The new configuration is the old configuration with the unresponsive replica removed. The overhead is the same as that of any update operation on the sequencer shard. Next, in order to restore the original level of fault tolerance, a new replica is allocated, placed at the end of the chain, and set to inherit the state of a replica in the current configuration in the background. Finally, once the new replica has the same persistent history as a replica in the current configuration, the sequencer wedges the current shard configura-

tion and issues a new configuration with the new replica at the tail of the chain of the old configuration.

Replicas in a new configuration can inherit the state of any wedged replica in the predecessor configuration. In our implementation, replicas of a new shard configuration issue an anycast request to all replicas of the predecessor configuration and adopt the history of the first responder.

If a sequencer fails during reconfiguration, system safety is not compromised. This is because elastic replication requires all replicas of a configuration to be active for any replica to change its persistent history. Replicas of a configuration become active only by successfully inheriting the history of a replica in a prior configuration. Thus, the worst affect of a failed sequencer is failure to notify all new replicas of a configuration to inherit the state of their predecessor configuration, which would result in an inactive shard configuration.

Elastic replication assumes that clients learn about shards and their configuration through out-of-band routing methods. Clients include the expected configuration id with their requests. If a replica receives a request with a configuration id not matching its own, it ignores the request and responds to the client with its current configuration.

4.1.9 Comparing ER with other protocols

We now briefly discuss how elastic replication (ER) compares to other crash-tolerant replication protocols, such as Primary-Backup (PB) [22,40], Chain Replication (CR) [116], asynchronous consensus techniques such as Paxos [75], Vertical Paxos [76], and Quorum Intersection (QI) techniques that provide strong consistency such as found in [26, 67, 113]. We also compare ER against the CRC

	PB/CR	QI	Paxos	Vertical Paxos	CRC Shuttle	ER
minimum # replicas needed	$f+1$	$2f+1$	$2f+1$	$f+1$	$f+1$	$f+1$
strongest consistency provided	linearizable	atomic R/W	linearizable	linearizable	linearizable	linearizable
requires accurate fault detection	yes	no	no	no	no	no
uses timeouts for liveness	yes	no	yes	yes	yes	yes
requires external configuration	yes	no	no	yes	yes	no
signatures required	none	none	none	none	CRC	none

Table 4.1: Comparison of replication protocols

Comparison of Primary-Backup (PB), Chain Replication (CR), Quorum Intersection (QI), Paxos, Vertical Paxos, Byzantine Chain Replication (CRC Shuttle), and Elastic Replication (ER) protocols.

Shuttle implementation of Byzantine Chain Replication, which only tolerates crash and omission failures [115]. A summary is provided in Table 4.1.

PB and CR depend on accurate failure detection (i.e., fail-stop [104]). However, in practice, failure detection is implemented using timeouts. If timeouts are chosen conservatively, then the probability of mistakes will be small. But in the case of a failure, service availability is reduced substantially. If timeouts are chosen aggressively short, then outages are short, but mistakes are common and lead to inconsistencies (multiple primaries in the case of PB, or multiple chains in the case of CR).

Paxos, Vertical Paxos, CRC Shuttle, and ER do not suffer from this safety defect, because they do not depend on accurate failure detection. However, they rely on failure detection for liveness. In Paxos, a faulty leader must eventually be replaced by another, causing a so-called *view change*; in Vertical Paxos, CRC Shuttle, and ER, a faulty replica must eventually be replaced, leading to a reconfiguration. The time to recover from a failure depends on the timeout used to detect failures. If chosen conservatively, then outages can be substantial. But aggressively chosen timeouts can lead to starvation. In practice, timeouts should be adaptive, so they are as short as practical, but no shorter.

Compared to ER, Paxos requires $2f+1$ replicas instead of only $f+1$.[1] Vertical Paxos requires only $f+1$ replicas for the read/write quorums but it relies on an auxiliary configuration master for reconfiguration. Byzantine Chain Replication provides two protocols: CRC Shuttle (which tolerates crash and omission failures) and HMAC Shuttle (which tolerates arbitrary failures). The specification of CRC Shuttle is similar to a single shard in ER, however it relies on an external configuration manager for reconfiguration while ER does not.

QI techniques do not rely on accurate failure detection and can completely mask failures altogether, requiring no timeouts. They are typically used to support read/overwrite operations on file-like objects, and provide atomic read/write register consistency. However, quorum systems can be used in conjunction with other protocols and synchronization mechanisms to implement a wide range of data semantics as demonstrated in [84]. See [72] for a comparison of quorum replication to other replication techniques. Also, consistent read operations are relatively expensive, since they require two round-trips of message exchange.

Like Paxos and other consensus techniques, QI protocols are based on majority voting, and thus they require a relatively large number of replicas. As in Paxos, techniques exist to make f of the replicas light-weight [91]. Nonetheless, such light-weight replicas still require independently failing resources (for a total of $2f+1$). On the other hand, ER leverages the existence of shards, each having $f+1$ replicas. ER explicitly does not work if there is only a single shard or even if all shards used the same $f+1$ locations for replication.

Any of these techniques can be made scalable through partitioning of data, since both linearizability and atomic R/W register semantics are *composable*; a

[1] In Paxos terms, there are $2f+1$ acceptors and $f+1$ learners that are typically co-located with acceptors. As acceptors have to maintain state for every command in the history, we consider them replicas.

system comprised of shards that provide linearizable consistency also provides linearizable consistency as a whole [59]. Also, all these techniques support weak forms of consistency for improved efficiency and liveness. For example, by allowing any replica to be read and buffering write operations at any replica [123].

4.2 Evaluation

In this section, we evaluate elastic replication analytically and experimentally. We analytically formulate the probability that the liveness condition for elastic replication is met, show its impact on system reliability, and compare the reliability of elastic replication with traditional methods using CCMs. Then, we benchmark a prototype distributed key-value store built using elastic replication.

4.2.1 Liveness condition

As mentioned in Section 4.1.5, elastic replication assumes that:

(A0) Each faulty replica is eventually suspected.

(A1) For any band, each shard contains at least one correct replica.

(A2) Each band always has at least one shard that has no replicas suspected of being faulty.

In our analysis, for simplicity, we assume that there are no false failure suspicions. In our implementation, we utilize existing literature on distributed-systems failure detectors [31,44,66,78,110]. For the sake of simplicity, we assume that our failure detector meets (A0) and focus on the other two assumptions.

(A1) and (A2) present an interesting trade-off: The smaller the band, the more likely assumption (A1) holds, whereas the larger the band, the more likely assumption (A2) holds. Another variable involved here is the number of replicas, n, in a shard. It suffers from a similar trade-off. The larger n is, the more likely that at least one replica is correct, but the less likely that there exists a shard consisting of only correct replicas.

Let p stand for the probability that a particular replica is correct, and let all configurations of all shards have disjoint sets of replicas with independent failure probabilities. Let $n = f + 1$ be the number of replicas in a shard. Then let $P_c = p^n$ be the probability that a shard is *correct*. Let $P_s = \sum_{i=1}^{n-1} \binom{n}{i} p^i (1-p)^{n-i} = 1 - (1-p)^n - P_c$ stand for the probability that a shard is *safe*, because between 1 and $n-1$ replicas are correct. If N denotes the number of shards on the band, then the probability that at least one shard has only correct replicas while the other shards each have at least one correct replica is:

$$P(p, n, N) = \sum_{i=1}^{N} \binom{N}{i} P_c^i \cdot P_s^{N-i} \tag{4.1}$$

This is exactly the probability that the liveness condition is met; typically one would require that $P(p, n, N) \geq (1 - \epsilon)$ for some small constant ϵ. If the liveness condition is not met, the system would require external intervention.

To demonstrate the feasibility of meeting the liveness condition, Figure 4.5 plots $1 - P(0.99, n, N)$ for various shard sizes (n) and number of shards (N). The 0.99 replica correctness probability was chosen to reflect the industry reliability assumptions of a conventional server [18]. The sharp dip followed by slow rise seen in Figure 4.5 arises from the tension between shard size and number of shards on the probability of meeting the liveness condition.

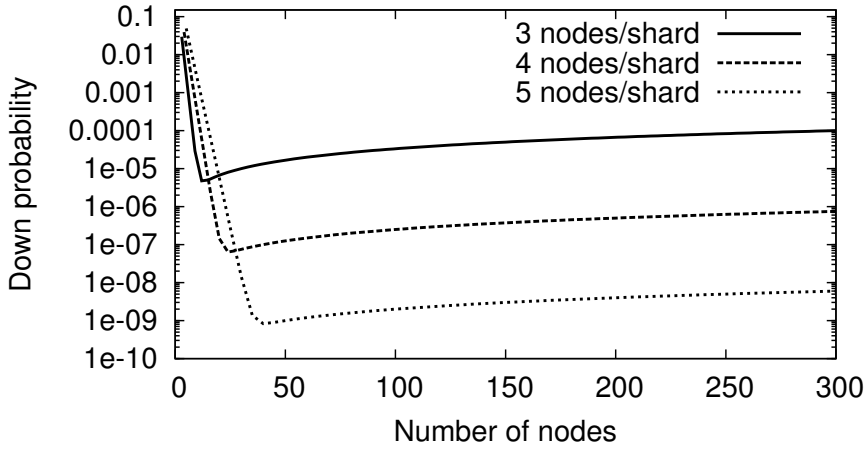


Figure 4.5: Probability of violating the liveness condition

Probability that the liveness condition is not met, so band requires external intervention, as a function of the number of replicas and size of shards. Shard replicas are assumed to be correct with probability $p = 0.99$.

4.2.2 Elastic replication vs. CCM

Elastic replication delegates the task of managing configurations to the shards in the system. Is this more reliable than using a CCM?

A sharded service managed by a CCM still has to meet liveness condition (A1), but condition (A2) is replaced with (A3): The requirement that centralized configuration manager does not fail. A replicated CCM running a quorum-based consensus protocol requires more than half of its replicas to be correct for liveness. Let m be the number of replicas in a CCM and p the probability that a replica is correct, then

$$Q(p, m) = \sum_{i=\lfloor 1+m/2 \rfloor}^{m} \binom{m}{i} p^i \cdot (1-p)^{m-i}$$

is the probability that a replicated CCM is up. Then the probability that a CCM-managed system does not require external intervention, is precisely the probability that (A1) and (A3) are met:

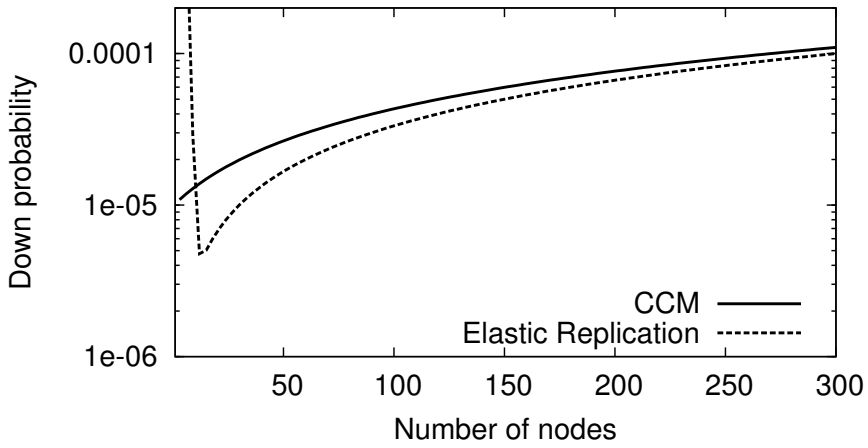


Figure 4.6: CCM vs elastic band

Probability that a system gets stuck requiring external intervention. An elastic replication deployment is compared to a collection of shards managed by a CCM comprised of 5 replicas. Each shard has 3 replicas. All replicas are assumed to have 99% uptime.

$$Q(p,m)\cdot\left(1-\sum_{i=1}^{N}\binom{N}{i}(1-p)^{i\cdot n}\cdot(1-(1-p)^{n})^{N-i}\right)$$

Figure 4.6 compares the probability that external intervention is required, because the liveness condition is not met, for an elastic band and a CCM-managed system. As the figure shows, a single self-managing elastic band is more reliable than a CCM for systems with more than 10 replicas.

4.2.3 Experimental setup

We now highlight some of the performance characteristics of elastic replication. To compare elastic replication to other protocols, we developed an application library that implements multiple replication protocols. The library defines a generic state machine module for user applications to customize. The module is comprised of functions to handle client commands as well as to initialize, export, and import the user application's state.

	Read	Write
Throughput (ops/sec)	16,385	12,894
Latency (msec)	6.64	8.94

Table 4.2: Stand-alone instance performance

Performance of a single stand-alone instance of our example storage server servicing read/write requests of 2KB objects from a network client and storing them in an Erlang DETS on disk.

The library is written in Erlang [23], and the following examples sketch a simple distributed service that stores and retrieves binary data to/from disk. The service is implemented as a server module that relies on our library for replication and sharding. Our focus is on the protocol layer, so the implementation relies on Erlang's built-in Disk Term Storage abstraction (DETS) for storage. To put our results in perspective, Table 4.2 shows the performance profile of running a stand-alone instance of our system on a single server servicing read and write requests for 2KB objects from a network client.

Our experiments ran on a 25-machine cluster. Each machine had an Intel Xeon Quad Core processor, 4GB of RAM, a 250GB SATA drive, and a quad port PCIe Intel Gigabit Ethernet card. The machines ran 64-bit Ubuntu 12.04 and Erlang R16B. The machines were connected via a Gigabit Ethernet network. Graph results represent the average of 10 runs and the error bars represent a standard deviation unit. We believe 10 runs per experiment were enough to get accurate trends because the variance across different runs in the same experiment was low.

4.2.4 Key-value store overview

A Key-Value Store (KVS) is a common storage abstraction in today's datacenters. It maps key from a predefined key space to an arbitrary data object. A

distributed KVS partitions the key space into a set of non-overlapping ranges– i.e., every key is mapped to exactly one range. The ranges are mapped onto shards such that each shard stores keys for a particular range $[p, q)$ in the key space. In steady state, the shard covering $[p, q)$ serves as the sequencer for the adjacent shard covering $[q, r)$, and thus forming an elastic band.

Two important management operations on shards are *split* and *merge*. Given a shard x covering $[p, r)$ and a key $q \in [p, r)$, the function *split*(x, q) results in shard x covering $[p, q)$ and a new shard x' covering $[q, r)$. For efficiency, shards x and x' will have replicas on the same set of hosts initially, but using reconfiguration the set of hosts can be updated subsequently. If x was sequencing the configuration for some shard y, then after the split x is sequencing x', and x' is sequencing y.

Given a shard x covering $[p, q)$ and a shard x' covering $[q, r)$, with x sequencing x', the function *merge*(x) results in x covering $[p, r)$. If x' was sequencing shard y, then after the configuration the sequencing of y is taken over by x. Shard x' can subsequently be garbage collected.

Using *split* and *merge*, it is possible to maintain a scalable and linearizable KVS [2]. We note that the composition of linearizable objects is linearizable, consequently the KVS is linearizable.

4.2.5 Single shard performance

We first measure the performance of a single shard in isolation as a function of the number of its replicas. Figure 4.7 shows the average read and write throughput for a single shard processing requests from 100 concurrent clients storing

[2]Observe that linearizability is a stronger property than required by a KVS; atomic R/W consistency suffices. However, protocols for atomic R/W consistency, such as [26] require $2f + 1$ replicas and multiple round-trips for `get` operations. Also, linearizability allows us to support operations beyond `put` and `get` only.

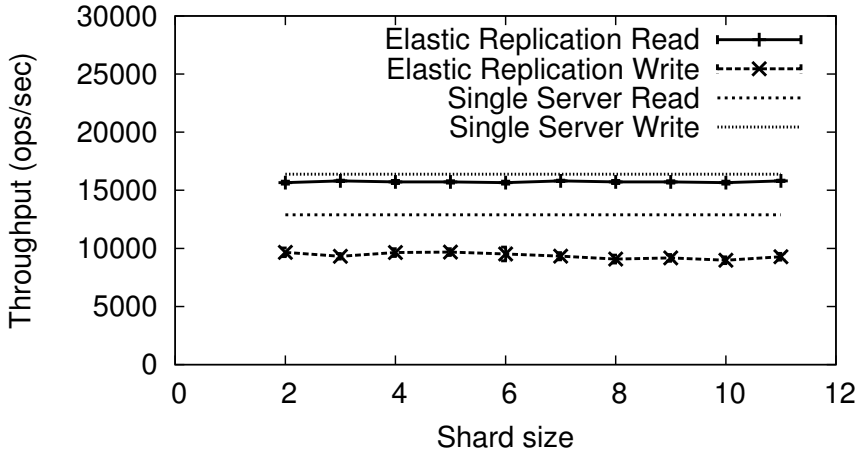


Figure 4.7: Shard read/write throughput

Average read/write throughput of per shard for elastic replication as a function of the number of replicas. The read/write throughput of a single unreplicated server is also plotted.

and retrieving 2KB objects. Our implementation of elastic replication is based on chain replication and thus exhibits similar throughput characteristics. The throughput of a single unreplicated server, as listed in Table 4.2, is also plotted in Figure 4.7 to highlight the overhead of Elastic Replication.

A concern with elastic replication is that in order to guarantee linearizability in the presence of failures, requests must propagate to all replicas in a configuration before execution. This applies to both read and write requests. How costly is that propagation?

To lower that cost, our implementation tags each request with the index number of the configuration that the client assumes for the shard. Before forwarding a command, each elastic replica checks that the tagged version number matches its own. If not, the request is dropped and the client is notified of the new configuration. With that, non-tail replicas handle read requests by just checking the request tag before forwarding it to their chain successor (without adding the request to the local unstable history queue or executing). When the

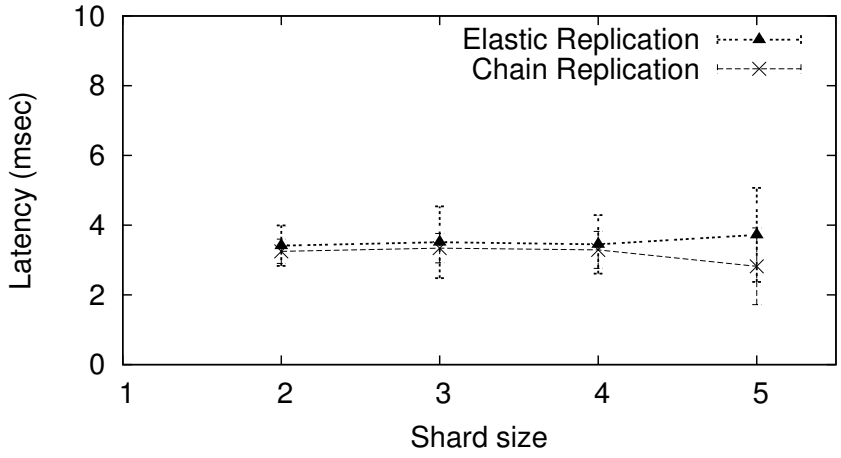


Figure 4.8: Shard read latency

95th percentile latency for *ping read* requests per shard as a function of the number replicas.

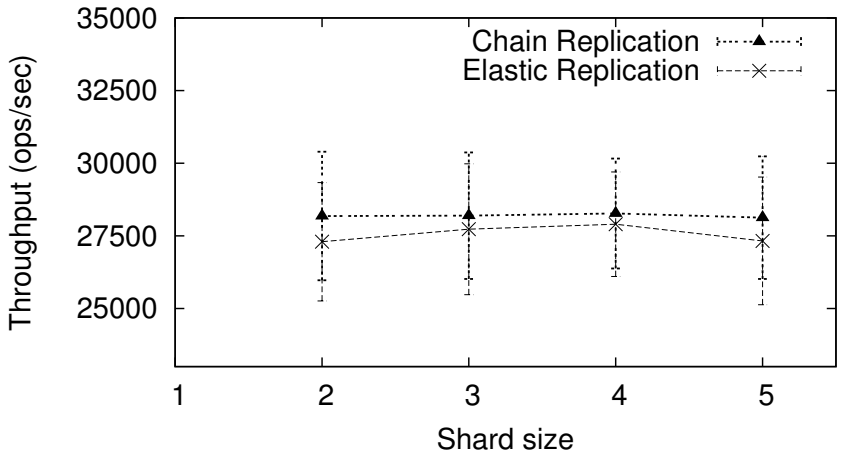


Figure 4.9: Shard read throughput

Average throughput of *ping read* requests per shard as a function of the number replicas.

tail receives a request, it checks the tag and responds to the client. This is a slight deviation from the original specification of elastic replication, which is agnostic to read/write request. But the modified scheme results in a performance benefit.

In our implementation, the cost of pipelining read requests to replicas is dominated by the cost of reading from the disk at the tail. To measure the cost

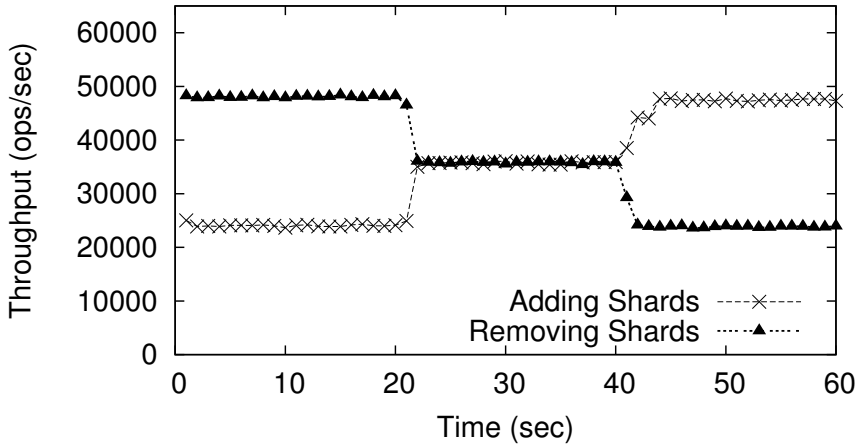


Figure 4.10: Throughput during elastic band reconfiguration

Impact of reconfiguration to add/remove shards on aggregate throughput. A partition was added/removed to the system every 20 seconds. When adding shards, the band originally had 2 shards, and when removing it started with 4 shards.

of propagating read requests, we made our clients send "ping read" requests to the replicated shard. These requests are treated by the replication protocol as a normal read request, but the underlying server responds without engaging the disk store. Figures 4.8 and 4.9 show the latency and throughput of handling ping read requests using both elastic replication and chain replication. As the figures demonstrate, the overhead of piping read requests through the chain is small. Elastic replication performs comparably to chain replication. The added cost is well within the margin of error.

The main conclusion here is that elastic replication has comparable high performance characteristics to chain replication, albeit with minimal overhead cost.

4.2.6 Band maintenance

Because a shard's configuration is separate from its other state, reconfiguration in elastic replication is cheap. Figure 4.10 shows a simple elastic band being

reconfigured to add/remove a shard every 20 seconds. This operation is trivial and barely has any impact on system throughput beyond the effects of adding or removing a shard.

Another technique for reconfiguring an elastic band is by merging/splitting shards. This technique allows part of the state of a large shard to be transfered to a new shard. We support two methods of state transfer: one-shot state transfer, and on-demand state transfer. In one-shot transfer, a newly created replica blocks until it receives all of its seed state from another replica or shard. In on-demand transfer, the newly created replica asynchronously receives its seed state "block-by-block" at a specified transfer rate.

A problem with on-demand transfer, however, is that incoming client requests might attempt to access parts of state that have not yet been transferred. We handle this issue in one of two ways: if the incoming request is write-only and completely overrides the unavailable block of original state, then that request is accepted and the block that it modified is marked as up-to-date. If not, the replica does a page-fetch of the block relevant to the client request and then executes that client request. On-demand paging relies on an appropriate application-specific definition of "data block". For our prototype key-value store, a data block is just a single key-value pair. In practice, more sophisticated locality-aware mechanisms might be used.

Figure 4.11 shows the impact of splitting/merging a shard every 20 seconds on an elastic band with on-demand state transfer. The cost of merging shards is larger than just removing them, because of the state transfer. However, in our implementation, background state-transfer mitigates the potential high cost.

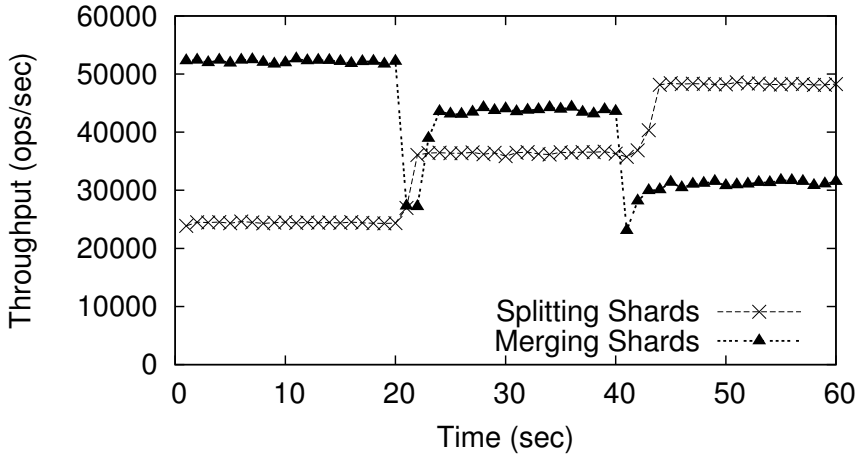


Figure 4.11: Throughput during shard split/merge

Impact of reconfiguration to split/merge shards on aggregate throughput. The split/merge occurred at the 20 and 40 seconds marks. In the split case, the band originally had 2 shards. In the merge case, the band started with 4 shards.

4.2.7 Shard maintenance

When a replica is unresponsive, the configuration needs to be modified. In order to restore service immediately, the new configuration is simply the old configuration with the unresponsive replica removed. The overhead is the same as that of any update operation on the sequencer shard. Next, in order to restore the original fault tolerance, a new replica needs to be allocated. Placement for optimal diversity and load balancing consideration need to be considered in that allocation. Then, a second reconfiguration adds the new replica to the configuration.

Figure 4.12 shows the impact of adding/removing replicas to a single shard through reconfiguration. The temporary drop in throughput, at the 20 seconds and 40 seconds time marks, is due to the original configuration being wedged. Because the choice of timeout values does not affect system safety, clients were using 5 second timeouts to retry requests. Requests to the old configuration (before adding/removing replicas) would timeout. When a client's request times

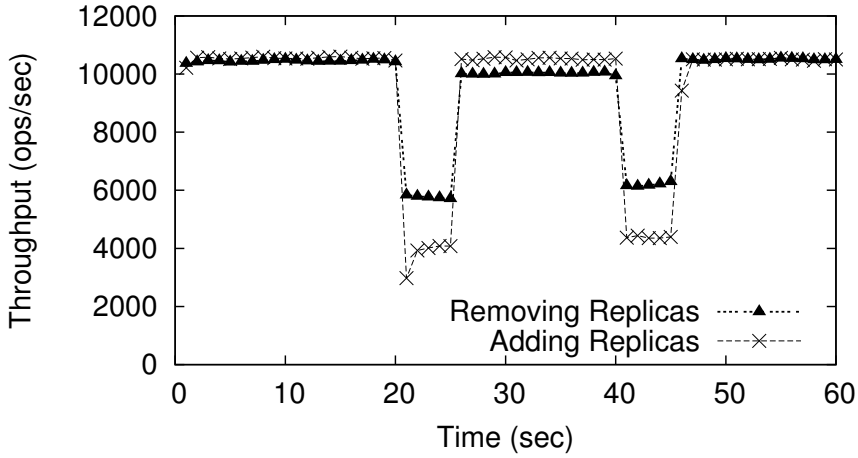


Figure 4.12: Throughput during shard reconfiguration

Impact of reconfiguration to add/remove replicas to a shard. Replicas were added/removed every 20 seconds.

out, it tries to refresh its configuration information by broadcasting a request to all the replicas of the old shard configuration. By our assumptions, at least one replica of the old configuration would still be correct and would know of the new configuration and responds to the client. Once the client receives a response detailing the new shard configuration, it retries its request.

4.2.8 Failure tolerance

Replicas in each shard monitor the replicas in the shard they are sequencing. When replica failure is suspected, the wedge command is issued to the victim shard by both the suspecting replicas in the same shard and the sequencer shard. This is done to prevent the shard from accepting any new client requests and guarantee that safety is not violated. Next, the sequencer issues a reconfiguration of the wedged shard and spins up new replicas if needed. Due to elastic replication's design, the choice of timeout value for failure detection only impacts the perceived latency and throughput of client requests but not the con-

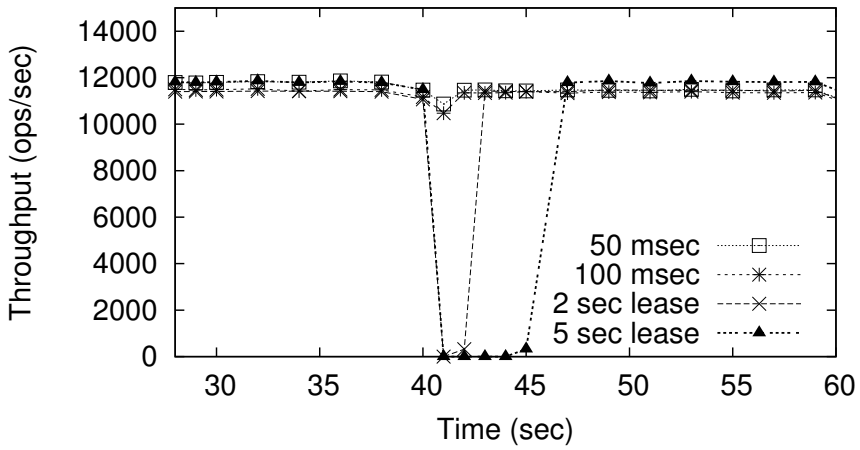


Figure 4.13: Downtime due to replica failure

Failure tolerance within a shard with various timeouts. Failure was induced at the 40th second. Shorter timeouts only result in shorter downtime without compromising safety.

sistency or the correctness of the system. Figure 4.13 highlights the impact of different timeout values on client throughput.

CHAPTER 5

FUTURE DIRECTIONS: UNIFIED PARTITIONING

A *Service-Level Objective* (SLO) is a collection of measurable capacity, performance, and reliability objectives that a datacenter system must meet. Paying customers of cloud computing services agree to *Service-Level Agreements* (SLAs) specifying SLOs in addition to contractual matters such as costs, responsibilities, and other general conditions.

No single machine is large, fast, or reliable enough to run a scalable cloud-based service. The key to scalability is partitioning the service's state, computation, and reliability requirements into smaller chunks. This can be accomplished by replication and sharding protocols. However, today's systems combine replication and sharding in only a limited way: In services internal to a datacenter, a hash function is typically used to partition state into shards of approximately the same size; then each shard is replicated onto multiple machines using some replication protocol. Powerful machines might be responsible for more shards than small machines, often by a large machine masquerading as a set of small machines (or "virtual nodes"), creating unnecessary complexity and overhead. Because of this construction, we dub this approach "shard-then-replicate".

A different design pattern is used for services across datacenters. Pragmatically, a system designer might want each datacenter to store a replica of the entire state. However, due to heterogeneity, different datacenters might use different replication and sharding schemes to provide the desired level of latency, throughput, and reliability. For example, a datacenter with powerful and reliable servers might partition its replica into a few shards, while another datacenter with low-end servers might create many replicated shards. We dub this approach "replicate-then-shard".

Neither approach methodically constructs systems to meet SLOs. This results in complications when systems are maintained, machines are replaced, or software upgraded and redeployed. In this chapter, we propose a modular approach to sharding and replication in datacenter and georeplicated cloud services. In order to meet a particular SLO given a heterogeneous set of resources, a system designer follows a top-down "partition-and-conquer" approach, starting with a high-level specification of the required service-level objectives, and refining that into an implementation with nested replication and sharding protocols. At each level, the SLO is weakened by the application of replication or sharding—until it can be satisfied by existing machines or services. We believe that this model would not only make it easier to build datacenter systems, but it would also make it possible to verify that an SLO is still satisfied after system modification or maintenance.

Our modular approach, *Unified Partitioning*, is a generalization of replication and sharding, employing *Partitioned State Machines* to complement Replicated State Machines, and *Service State Machines* to incorporate SLOs into the model. Partitioned State Machines are designed to be nested, with ordinary deterministic state machines forming the base case.

5.1 System Model and Terminology

Two basic building blocks are used in our model: The *Service State Machine* (SSM) and the *Engine*. Intuitively, an SSM is a state machine with operational SLO requirements, and an engine is a machine or service that is capable of running the SSM and meeting its SLO requirements. Not all engines are capable of running all SSMs.

A *finite-state transducer* is a finite-state machine with an input tape and an output tape—i.e., it reads inputs and produces outputs. Formally, a finite-state transducer, σ, is defined as a sextuple $(\Sigma, \Gamma, S, s_0, \delta, \omega)$, where:

- Σ is the input alphabet (an alphabet is a finite non-empty set, the elements of which are called symbols).
- Γ is the output alphabet.
- S is a finite, non-empty, set of states.
- $s_0 \in S$ is an initial set.
- $\delta : S \times \Sigma \to S$ is the state-transition function.
- ω is the output function. If $\omega : S \times \Sigma \to \Gamma$, then σ is called a *Mealy machine*. If $\omega : S \to \Gamma$, then σ is called a *Moore machine*.

A *Service state machine* (SSM), $\mathcal{S}$, is defined as a septuple: $(\Sigma, \Gamma, S, s_0, \delta, \omega, \text{SLO})$. SLO is a *Service-level objective*, which specifies measurable metrics required by the service $\mathcal{S}$, such as how much storage is needed to run $\mathcal{S}$, how many inputs per second it should be able to handle, and its reliability characteristics. For example, an SLO can be a triple $(50 \text{ PB}, 50000 \text{ ops/sec}, < 5 \text{ minutes of downtime per year})$. SLOs could be extended to represent other metrics. To simplify notation, $\mathcal{S}$ is shorthanded as (σ, SLO).

An SSM is just a description. An engine is what runs an SSM. Each engine $\mathcal{E}$ has a particular *capability* that describes which SLOs the engine can satisfy. An engine runs at most one SSM, maintaining state and producing outputs in response to a sequence of inputs, assuming that the engine's capabilities satisfy the SSM's SLO. The inputs to an SSM are external messages and output messages produced by engines running other SSMs.

5.2 Partitioned State Machines

An engine might not be able to satisfy the SLO of an SSM in terms of storage, performance characteristics, reliability, or any combination thereof. However, a collection of engines running a "distributed version of the SSM" might be able to satisfy the SLO. In effect, the collection of engines emulate a more powerful engine. Each of the engines is running an SSM of its own.

A *Partitioned Service State Machine* (PSSM) is a formulation of a distributed SSM. To understand what a PSSM is, we first introduce the concept of a PSM. A *Partitioned State Machine* (PSM) is described by a tuple $\mathcal{S} = (V, \rho, \pi)$ where:

1. V is a vector of State Machines (SMs) as defined previously.
2. $\rho : \bigcup_\sigma \Sigma \times V \rightarrow \hat{\sigma}$ is a routing function that assigns each input to one or more state machine $\sigma \in \hat{\sigma}$ in V.
3. $\pi : \bigcup_\sigma \Sigma \times V \rightarrow$ `true | false` is a boolean *filtering* function on the output of the state machines in V.

In a PSM, $\mathcal{S}$, an input i is applied to $V[\rho(i)]$ and updates only the state of that SM. The output set of $\mathcal{S}$ is the union of the output sets of each member in V filtered by π—the other outputs produced are used internally to the PSM.

A Replicated State Machine (RSM) [105] is an example of a Partitioned State Machine, partitioning the reliability requirements across a set of replica SMs. An RSM can be automatically generated from a deterministic state machine using a protocol such as Paxos [75]. In this case, V is a collection of SMs—some replicas of a SM $\mathcal{S}$, and some Paxos acceptors. The routing function assigns each input to all acceptors, each an SM in its own right. Output of the acceptors are filtered out by the filtering function, leaving only the outputs of the replica SMs in V.

Another example of a PSM is what we call a *Sharded State Machine*, useful for implementing systems with state, too large to run within a single machine efficiently. A distributed key-value store is a good example of such system. If (V, ρ, π) is a Sharded State Machine, each entry in V starts out with the same deterministic state machine that implements the key-value store. Routing function ρ, in this case, is a hash function that assigns each input to one of the entry in V, and π a function that always returns `true`. Thus the output of the Sharded State Machine is the union of the outputs of the SMs in V.

PSMs may be nested. If (V, ρ, π) is a PSM, then the SMs in V may themselves be PSMs. In the case of the key-value store example, the entire store could be viewed as a single SM, its state formed by all current key-value pairs, its transition function the query and update operations available on keys, and its output set simply the set of results produced by those operations. But the KVS is typically both sharded and replicated. A traditional "shard-then-replicate" approach to a scalable and reliable Key-Value Store can be implemented by nesting replicated state machines within a sharded state machine, replicating each shard. Nesting can be done arbitrarily deep. A *PTree* is a tree of nested PSMs.

A PSSM is a service state machine that extends PSM to account for SLO requirements. A PSSM is described by the four-tuple $(\mathcal{V}, \rho, \pi, \text{SLO})$ where $\mathcal{V}$ is a vector of service state machines. The SLOs of the members of $\mathcal{V}$ represent weaker requirements than those of their parent PSSM. For example, the SLOs of SSMs in $\mathcal{V}$ for a sharding protocol will have aggregate capacity that meet or exceed the capacity requirement of the parent PSSM. For a replication protocol, the SLOs of $\mathcal{V}$ will have weaker reliability requirements than those of the parent. The specifics of breaking down SLOs at each level will depend on the particular replication or sharding protocol and are beyond the scope of this chapter.

Another interesting future works direction is monitoring services at runtime to ensure that SLOs are met, and automatically taking corrective actions if they are not. We see that value of our proposed model in that it augments replicated and sharded state machines with SLO requirements, is just as expressive as ad-hoc techniques such as virtual nodes, and it allows expressing specific SLO requirements for different levels of the system.

Nesting PSSMs is related to *Finite-State Machine Decomposition*; where a state machine is decomposed into a collection of smaller state machines [25, 47, 54, 55, 61, 65]. This is heavily used in application-specific integrated-circuits, and integrated-circuit design in general, in order to optimize the logic circuit representing the FSM for low power, reducing area, wire lengths, reusing circuit components, and satisfying other fabrication requirements. FSM decomposition and PSSM decomposition are both used to meet deployment constraints. However, nesting PSSMs is different from FSM decomposition in that the nested service state-machines are not simpler, but rather have weaker SLOs. This is because PSSM decomposition introduces a new replication or sharding protocol at every level of the decomposition, in order to weaken the SLO to meet the capabilities of available engines.

5.3 Current Status

Unified partitioning emerged during the course of our work on comparing multiple replication protocols including elastic replication and Pileus [112]. We created a programming library (*libdist*) for comparing different protocols and system designs under one common implementation. Later, the library was rewritten to support nested sharding and replication via unified partitioning. The evaluation results presented in Chapter 4 were rerun on libdist to make sure

that the library works and there were no significant performance penalties. In those experiments, elastic replication was re-implemented as nesting of an intra-shard replication protocol and an inter-shard sharding protocol for elastic band management. The performance results were similar to what was reported in Section 4.2 with a negligible penalty hit of a few Erlang reductions [24] due to nesting.

5.3.1 libdist overview

Libdist is a library for building sharded and replicated distributed systems. Libdist implements a suite of replication protocols as well as a simple sharding protocol with support for one-hop routing to the different shards. Additionally, libdist handles instantiating server processes, monitoring processes, failure handling, tracking configuration changes, and client interaction with the system. To use libdist, a developer implements a state machine interface that is exposed by the library. The developer then specifies the desired sharding/replication protocol to be used as well as a list of host machines that are available to run the system. Libdist then wraps the developer's state machine module with the specified protocol, deploys it on the machines, and returns a configuration handle that clients can use to interact with the system.

Table 5.1 shows the state machine interface that is exposed by libdist. It is comprised of functions to initialize the system's state, handle incoming client commands, check whether a command is read-only or not, serialize and reconstruct all or part of the state, as well as handling termination and state clean-up.

We chose to apply partitioning at the granularity of a single process state. This approach is easier to implement and more flexible than nesting at a coarser grain, e.g. sharding the whole of a replicated system. To implement partition-

Function	Input	Output
`init_sm`	Initialization parameters	State
`handle_cmd`	State, Command, AllowSideEffects	New State
`is_mutating`	Command	`true`|`false`
`stop`	State, Reason	`success`|`failure`
`export`	State	Serialized state
`export`	State, Condition	Serialized part of the state where condition holds true
`import`	Seralized State	State

Table 5.1: *libdist* state machine interface

ing at the granularity of a single process, it is helpful to separate the state of the protocol from that of the application. For example, in a replicated state machine system with three replicas, there are six "execution engines" at work: three to run and maintain the replication protocol's state, and another three to run and maintain copies of the application's state. Let's assume that the replicated application is a key-value store; the application state is a list of key-value pairs. We can shard any copy of the application state, but we might not be able to shard the state of replication protocol without compromising its correctness. Here, separating replication state from application state leads to a clean "replicate-then-shard" nested construction, where the state of the key-value store is sharded, but the replication state is not.

To implement protocol nesting, every process in a libdist distributed system is comprised of three threads: A *receiving thread*, a *protocol thread*, and an *application thread*. The receiving thread is implemented as a performance optimization, and it is responsible only for taking incoming messages from the networking stack and storing them in a queue that is constantly checked by the protocol thread. The protocol thread maintains the state of the partitioning protocol, processes protocol-related messages, and offloads application-related messages

to the application thread which, in turn, maintains the application state and processes related messages.

Libdist supports introducing a new level of nesting to a running system by partitioning an existing process. Because unified partitioning is always applied at the granularity of a single process's state, nesting always happens at the leaf of a PTree.

To partition the state of an existing process p on a set of machines M using protocol q, new processes are spawned on machines M and configured to use protocol q. Let the resulting configuration be C. Next, an *inherit* command is sent to p, which thereafter will not accept further commands modifying its application state. Then, p serializes the application state using its implementation of the defined state machine interface, and it transfers that state to processes in C. After the state transfer is completed, p modifies the current PTree by traversing a to the root. At each node, it replaces its address with that of C and notifies the node's siblings of the change. Once traversal reaches the root, the partitioning is complete.

Partitioning a running process can result in complications to clients and other existing processes in the system. To address that, two techniques are used in our implementation: First, processes in the system communicate with one another using *communication stubs*. When a process is partitioned, its communication stub is updated at other processes in the system during PTree reconfiguration. The new stub communicates based on the partitioning protocol. Since unified partitioning allows for nesting, communication stubs can be nested as well. A process communicating with a component that is implemented as a sharded replicated service uses a protocol-specific replication stub nested in a sharding stub.

Second, partitioning components can result in unintended side-effects. For example, a component that is expected to produce a single network message upon receiving a client command could produce multiple messages if it were replicated. The method to handle client commands in the state machine interface exposed by libdist therefore includes a flag to specify whether side-effects should be suppressed by the current process. That flag is set by the implementation of the different replication and sharding protocols in a way that the side-effect will only be produced when the command is to considered to have been handled by the partitioned state machine as a whole. Because replication and sharding protocols implement libdist's state machine interface, nesting these protocols does not result in unwanted extra side-effects.

The library is actively maintained and the code is available publicly at: `https://github.com/hussamal/libdist`.

5.4 Discussion

Having proposed a model, we discuss two use cases of nesting replication protocols to improve performance and reliability. Then, we close with other future directions.

5.4.1 Hybrid replication protocols

Replication protocols can be combined using unified partitioning to create new hybrid protocols that exhibit improved performance characteristics. For example, chain replication provides linearizable consistency semantics and tolerates the failure of all but one replica, but its read throughput is limited to that of a single replica. Consider a chain of length two, where the tail of the chain

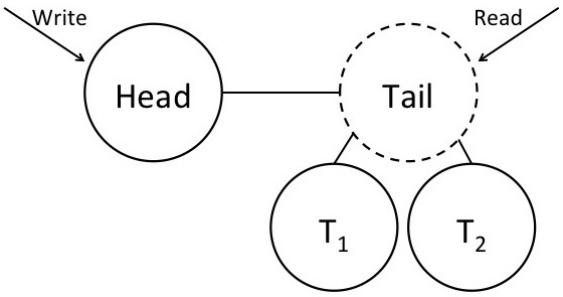


Figure 5.1: Architectural view of a chain/broadcast hybrid protocol

is itself a two-replica system running a protocol that broadcasts writes to both replicas and randomly directs reads to one of those replicas. This protocol is similar to a quorum intersection protocol but it makes the stronger failure detection assumptions of chain replication, and relies on an external master for reconfiguration—as does the chain replication protocol. Figure 5.1 shows an example of this setup.

Operationally, a client's write requests is sent to the head of the chain just like traditional chain replication. The head then forwards the request to the tail node. Because the tail node is a replicated system, the head's message is broadcast to processes T_1 and T_2 in Figure 5.1 which in turn execute the write and respond to the client. The client's communication stub waits for receiving both responses before considering the write to have completed.

Read requests are forwarded to the tail, as in traditional chain replication. However, again, because the tail node is a replicated system where reads are supported by all replicas, the client has the option of either broadcasting read requests to all tail replicas and waiting for the first response, or trying one replica at a time and switching to the other one in case of a timeout. The latter approach splits the read load across the tail processes and thus improves read throughput.

To demonstrate the performance improvement, we implemented this hybrid protocol and compared its read throughput against that of chain replication and

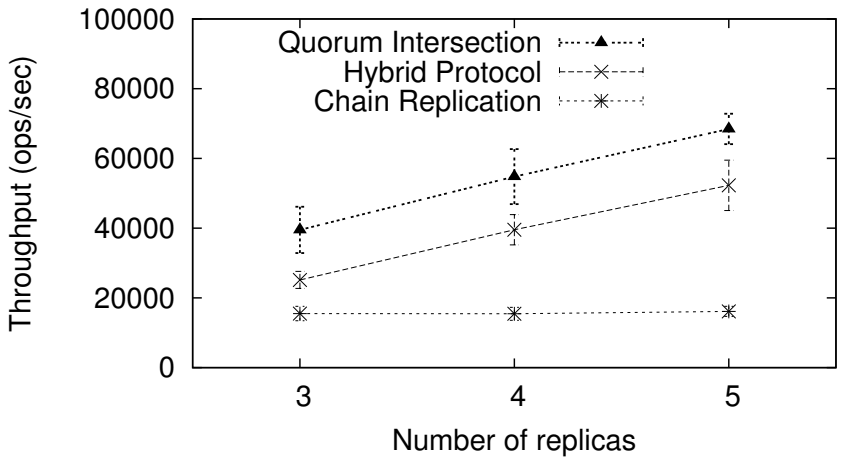


Figure 5.2: Read throughput the hybrid protocol

A comparison of the read throughput of the hybrid protocol and its constituting parts: Chain replication, and quorum intersection. The average of 10 runs is shown, and the standard deviation is shown by the error bars above and below each data point.

quorum intersection configured to write-all-read-any for a few deployments, as reported in Figure 5.2.

Architecturally, the hybrid protocol looks like a multi-tailed chain. However, there are two important things to note here: First, we did not *implement* a new protocol, but instead, we *nested* two protocols that are unaware of each other. Chain replication operates at the top level unaware of the nested protocol, and the nested protocol operates at the lower level unaware of the top-level protocol. Second, even though this hybrid protocol resembles an instance of a primary/backup system [22], reads in primary/backup are handled by the primary replica in order to guarantee linearizable consistency, but reads in the hybrid protocol reads are handled by any one of the tail replicas.

5.4.2 Availability of flat and nested quorums

Systems are often deployed across multiple failure domains, such as server racks and datacenters to protect against correlated failures. For example, a system might split its processes across servers on multiple server racks to tolerate rack-level power or network failures. Another example would be to replicate data across geographically dispersed datacenters to tolerate failures due to natural disasters.

When replicating across multiple failure domains, developers are faced with a choice: Should replicas be grouped by failure domain or should they operate in a "flat structure"? The answer here depends on the reliability of servers and the failure domain. Figure 5.3 plots an example where 9 processes participate in a quorum intersection replicated system where every 3 processes are in a different failure domain. All servers are assumed to have the same reliability regardless of failure domain. The figure shows that, depending on the failure probability of individual servers and failure domains, transforming a flat quorum into a nested quorum results in higher overall system reliability.

5.4.3 Beyond new protocols

The top-down approach of creating a system using a PTree of PSSMs defines contracts between SSMs and engines: SSMs require certain SLOs, engines provide certain capacity, and the connecting protocols (in the form of PSSMs) ensure that the SSM SLOs are met by the engines they are mapped onto. In contrast, today's systems are often built from the bottom up, which makes it hard to reason about the expected performance and properties of components at design time. Using unified partitioning, we start with desired SLOs at the top level and recursively refine that until we reach the low-level components.

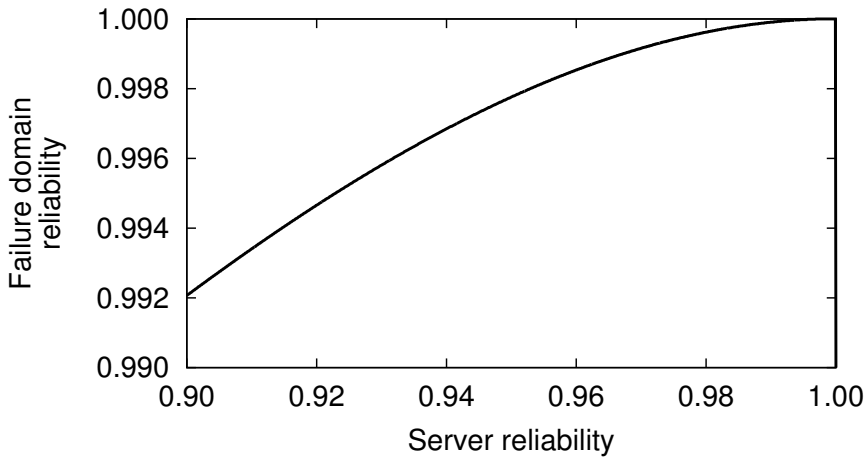


Figure 5.3: Availability of flat and nested 9-process quorums

In the area under the curve, nesting processes in three 3-process quorums per failure domain results in higher reliability of the overall system. In the area above the curve, a flat 9-process quorum across all failure domains is more reliable.

The presence of SLOs between the different levels of the PTree simplifies system maintenance. When an engine is replaced, the replacement must provide the capabilities requested by the SSM it runs. Otherwise, parts of the PTree may have to be redesigned, applying unified partitioning once again to obtain a new architecture suited for the available engines. Similarly, unified partitioning makes the composition of replication and partitioning in the implementation an explicit design decision rather than an implicit one, as it often is today. This simplifies reasoning about system properties.

Additionally, unified partitioning simplifies implementing replica placement policies. Replica placement impacts a system's performance, availability, and failure-tolerance. Even though there has been extensive research into replica placement strategies [46, 57, 60, 95], integrating these policies into a system's design remains tricky and ad-hoc [4, 5]. However, using nested replication and sharding in unified partitioning, a system designer can explicitly cre-

ate multiple copies of the system state and dictate which engines they run on explicitly—as long as these engines' capabilities can satisfy the different SLOs.

Because system replicas are explicitly defined in unified partitioning, they could be assigned different roles. For example, all client-facing operations could be routed to one replica of the system, whereas all back-end processing tasks are routed to a different replica. Similarly, clients could be made to only interact with one replica of the system. This could guarantee clients a stronger minimum consistency guarantee than just eventual consistency [79, 112]. For example, a client that always interacts with the same system replica can be given a Monotonic Read guarantee or even a Bounded-Delay guarantee, where requests are guaranteed to be consistent with time-bounded staleness—depending on the deployment and actual implementation of the replication protocol [112].

Finally, there are many possibilities of future work beyond creating new nested replication protocols. An interesting direction would be to use libdist to automatically build and maintain a PTree from a top-level SLO. This would require understanding how different protocols break down a required SLO into a collection of SLOs with weaker requirements. This might require a combination of analysis of protocol behavior and profiling the deployment environment with different protocols. Additionally, maintaining a deployed PTree would require a monitoring layer and a mechanism to audit potential violations of the SLO and act accordingly. Automatic deployments have been studied at the level of VMs and datacenter resources [71] but not at the level of protocols and system architecture.

CHAPTER 6

CONCLUSION AND RELATED WORK

The realities of datacenters and cloud services undoubtedly change how we build distributed systems. In this thesis, we explored new uses for well-known redundancy techniques.

Erasure coding can help protect cloud storage customers from vendor lock-in using schemes like RACS. The cloud services marketplace is in its infancy. While it might be at the forefront of technology, as a market—an *economic entity*—it is not unique. In cloud computing, it is fitting that technological devices should be used to address economic problems, and that is what RACS is: A simple application of technology to change the structure of a market. In RACS, consumers have a tool that can be used to adjust the trade-off between overhead expense and vendor mobility. In the design of RACS, we apply erasure coding to a different type of failure (economic) than it is usually used for in storage systems. We built a working implementation and ran microbenchmarks, and we simulated larger experiments on real-world traces. Based on these simulations and experiments, we conclude that RACS enables cloud storage customers to explore trade-offs between overhead and mobility, and to better exploit new developments in the fast-paced cloud storage marketplace.

As more, and larger, organizations turn to cloud computing service providers for their storage needs, it is imperative that these organizations be able to change storage providers, for any reason, without prohibitive costs (monetary, time, etc). RACS attempts to reduce the cost of switching storage providers. While the problem of optimally choosing from between competing vendors is related to the domain of Algorithmic Game Theory [88], our work

with RACS treats price hikes as failures, and uses data redundancy techniques (erasure coding) to protect against them.

RACS is similar to implementing RAID across cloud storage providers. HAIL [39] uses RAID-like techniques across storage providers to ensure high-availability and integrity of data stored in the cloud. Peer-to-peer storage [48, 50,51,97] employs RAID-like techniques to ensure availability and durability of data. The difference between systems like HAIL, peer-to-peer storage systems, and RACS, is that RACS focuses on economic failures and how to prevent them without excessive overheads, while still benefiting from greater availability and durability of other RAID-like systems.

IBM's Multi-cloud Storage Toolkit [29] leverages the heterogeneity of different cloud-storage providers to build a storage system with improved intrusion-tolerance. In a similar vein, Depot [83] makes minimal trust guarantees of cloud-storage services. Depot replicates data across storage providers to build a data store with Fork-Join-Causal consistency guarantees. DepSky [32] is similar to Depot, but it emphasizes data availability by making redundant copies across multiple cloud providers. SPANStore [122] focuses on using multiple storage providers for improved performance via geo-replication, and on cost reduction via price minimization strategies. Furthermore, Xen-blanket [121] works on computation across multiple cloud providers by allowing a virtual machine on one provider to migrate to another provider for reduced cost or improved performance.

Legislatively, the European Union will soon adopt a *General Data Protection Regulation* that stipulates, amongst other things, the right to data portability for the users of cloud-computing services. This law applies to personal data, and it would allow users to request a copy of their data hosted at a cloud-computing

service, obtain the data in a format usable by the person, and transmit it to a different cloud-computing service. By their nature, cloud-storage services allow customers to obtain a copy of their data and transmit it to a competing storage provider. RACS's motivation is that while data migration is possible between storage providers, it might be prohibitively costly. RACS reduces the cost of data migration and helps customers avoid vendor lock-in.

In the implementation of cloud storage services, techniques like Elastic replication leverage the sharded nature of datacenter systems to mitigate the cost of configuration management. It supports rapid reconfiguration without the use of a centralized configuration manager. Elastic replication is novel in that replicated shards are responsible for each others' configurations. Each shard uses only $f + 1$ replicas to tolerate up to f crash failures at a time. Elastic replication guarantees strong consistency in the presence of reconfiguration and without relying on accurate failure detection. We formally specified our new protocol, analyzed its reliability properties, and benchmarked a prototype implementation.

Elastic replication is best considered a scalable instantiation of the Replicated State Machine (RSM) approach [74, 105] in which a collection of replicas apply the same operations in the same order.

Various scalable peer-to-peer storage systems have proposed separating configuration from storage for improved consistency [77, 87, 100, 102]. Similarly, Vertical Paxos (VP) [76] uses an auxiliary configuration master to reconfigure primary-backup or read/write quorums. Another such approach is Dynamic Service Replication [36], a mixture of consensus and virtual synchrony-based [35] replication strategies. There are two important differences between these schemes and elastic replication. First, they rely on a majority-based con-

sensus protocol for reconfiguration, whereas elastic replication does not. Second, they use consensus not only to agree on the sequence of configurations but also to agree on the initial application state in each configuration. In elastic replication, replicas can be reconfigured without updating their application state.

Centralized configuration management services, such as Zookeeper and Chubby, use majority-based consensus protocols to serialize configurations, and the systems they manage rarely provide strong consistency guarantees. Also, many of these services provide only atomic read/write operations, while elastic replication supports the full deterministic state machine model.

Our work is similar to Vertical Paxos, wherein replicated state is separate from configuration. However, unlike Vertical Paxos, elastic replication does not rely on an external configuration master to reconfigure. Additionally, it does not require an instance of the consensus protocol to reconfigure. Furthermore, the use of shards to monitor and reconfigure each other is novel.

Scatter [63] is another system that is related to elastic replication. Scatter uses a ring of shards and provides linearizable consistency. Like elastic replication, Scatter also moves the task of managing shard configurations onto other shards. However, there are important differences between Scatter and elastic replication. Scatter uses Paxos in each shard, and reconfiguring a shard is done via a two-phase commit transaction that runs across the shards. This is not the case for elastic replication. Additionally, compared to elastic replication, Scatter requires almost double the number of replicas ($2f + 1$ instead of $f + 1$).

Finally, we presented a future work direction whereby replication and sharding are nested to support constructing datacenter systems that adhere to defined service-level objectives. We argued that our proposed model captures the ex-

pressiveness of existing techniques and supports new possibilities such as automatic deployments and SLO auditing.

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