Cost Analysis of Redundancy Schemes for Distributed Storage Systems

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Distributed storage infrastructures require the use of data redundancy to achieve high data reliability. Unfortunately, the use of redundancy introduces storage and communication overheads, which can either reduce the overall storage capacity of the system or increase its costs. To mitigate the storage and communication overhead, different redundancy schemes have been proposed. However, due to the great variety of underlying storage infrastructures and the different application needs, optimizing these redundancy schemes for each storage infrastructure is cumbersome. The lack of rules to determine the optimal level of redundancy for each storage configuration leads developers in industry to often choose simpler redundancy schemes, which are usually not the optimal ones. In this paper we analyze the cost of different redundancy schemes and derive a set of rules to determine which redundancy scheme minimizes the storage and the communication costs for a given system configuration. Additionally, we use simulation to show that theoretically-optimal schemes may not be viable in a realistic setting where nodes can go off-line and repairs may be delayed. In these cases, we identify which are the trade-offs between the storage and communication overheads of the redundancy scheme and its data reliability.

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1. INTRODUCTION

Distributed storage systems are widely used today for reasons of scalability and performance. There are distributed file-systems such as Google FS [Ghemawat et al. 2003], HDFS [Borthakur 2007], GPFS [Schmuck and Haskin 2002] or Dynamo [Hastorun et al. 2007] and peer-to-peer (P2P) storage applications like Wuala [WuaLa 2010] or OceanStore [Kubiatowicz et al. 2000].

To achieve high reliability in distributed storage systems, a certain level of data redundancy is required. Unfortunately, the use of redundancy increases the storage and communication costs of the system: (i) the space required to store each file is increased, and (ii) additional communication bandwidth is required to repair lost data. It is important to optimize redundancy schemes in order to minimize these storage and communication costs. For example, in data centers where the energy cost associated with the storage sub-system represents about 40% of the energy consumption of all the IT components [Guerra et al. 2010], minimizing storage cost can significantly reduce the per-byte cost of the storage system. Whereas in less-reliable infrastructures —i.e. P2P systems— where the storage capacity is mainly constrained by the cross-system communications...
bandwidth, minimizing communication costs can increase the overall storage capacity of the system.

Different redundancy schemes have been proposed to minimize the storage and communication costs associated with redundancy. Redundancy schemes based on coding techniques such as Reed-Solomon codes or LDPC allow to achieve significant storage savings as compared to simple replication. Moreover, recent advances in network coding have lead to the design of Regenerating Codes that allow to reduce both, the storage and communication costs, as compared to replication. While coding schemes can provide cost efficient redundancy in production environments, distributed storage designers are still slow in adapting advanced coding schemes for their systems. In our opinion, one reason for this reluctance is that coding schemes present too many configuration trade-offs that make it difficult to determine the optimal configuration for a given storage infrastructure.

Besides coding or replication one can also combine these two techniques into a hybrid redundancy scheme. In some circumstances these hybrid redundancy schemes can reduce the costs of coding schemes. Besides reducing costs, there are other reasons why maintaining whole file replicas in conjunction with encoded copies is advantageous: (i) production systems using replication that want to reduce their costs without migrating their whole infrastructure, (ii) peer-assisted cloud storage systems, like Wuala, that aim to reduce the outgoing cloud bandwidth by combining cloud-storage with P2P storage, and (iii) storage systems needing efficient file retrievals that cannot afford the computational costs inherent in coding schemes. Unfortunately, there are no studies analyzing under which conditions hybrid schemes can reduce the storage and communication costs as compared to simple replication.

Due to the great variety of redundancy schemes, it is complex to determine which redundancy scheme is the best for a given infrastructure that is defined by properties like size (number of storage nodes), amount of stored data, node dynamics, and cross-system bandwidth. The aim of this paper is to analyze the impact of different properties on the storage and communication costs of the redundancy scheme. We focus our analysis on Regenerating Codes. As we will see in Section 4, Regenerating Codes provide a generic framework that also allows us to analyze replication schemes and maximum-distance separable (MDS) codes such as Reed-Solomon codes as specific instances of Regenerating Codes.

The main contributions of our paper are as follows:

— This paper is the first to completely evaluate the storage and communication costs of Regenerating Codes under different system conditions.
— For storage systems that need to maintain whole replicas of the stored files, we identify the conditions where a hybrid scheme (replication+coding) can reduce the storage and communication costs of a simple replication scheme.
— Finally, we evaluate through simulation the effects that different redundancy scheme configurations have on the scalability of the storage system. We show that some theoretically-optimal schemes cannot guarantee data reliability in realistic storage environments.

The rest of the paper is organized as follows. In Section 2 we present the related work. In sections 3 and 4 we describe our storage model and Regenerating Codes. In Section 5 we analytically evaluate the storage and communication costs of Regenerating Codes. In Section 6 we analyze a hybrid redundancy scheme that combines Regenerating Codes and replication. Finally, in Section 7 we validate and extend our analytical results using simulations, and in Section 8 we state our conclusions.
2. RELATED WORK

Tolerating node failures is a key requirement to achieve data reliability in distributed storage systems. Existing distributed storage systems use different strategies to cope with these node failures depending on whether these failures are transient —nodes reconnect without losing any data— or permanent —nodes disconnect and lose their data. In this section we present the existing techniques used to alleviate the costs caused by these transient and permanent node failures.

Transient node failures cause temporal data unavailabilities that may prevent users from retrieving their stored files. To tolerate transient node failures and guarantee high data availability, storage systems need to introduce data redundancy. Redundancy ensures (with high probability) that files can be retrieved even when some storage nodes are temporally off-line. The simplest way to introduce redundancy is by replicating each stored file. However, redundancy schemes based on coding techniques can significantly reduce the amount of redundancy (and storage space) required while achieving the same data reliability [Weatherspoon and Kubiatowicz 2002; Bhagwan et al. 2002]. Lin et al. [Lin et al. 2004] showed that such a reduction in redundancy is only possible when node on-line availabilities are high. For example, nodes must be more than 50% of the time on-line when files are stored occupying twice their original size, or more than 33% of the time on-line when files occupy three times their original size.

To cope with permanent node failures, storage systems need to repair the lost redundancy. Unfortunately, repairing such lost redundancy introduces communication overheads since it requires to move large amounts of data between nodes. Blake and Rodrigues [Blake and Rodrigues 2003] demonstrated that the communication bandwidth used by these repairs can limit the scalability of the system in three main situations: (i) when the node failure rate is high, (ii) when the cross-system bandwidth is low, (iii) or when the system stores too much data. Additionally, Rodrigues and Liskov [Rodrigues and Liskov 2005] compared replication and erasure codes in terms of communications overheads and concluded that when on-line node availabilities are high, replication requires less communication than erasure codes. These results pose a dilemma for storage designers: when node on-line availabilities are high, erasure codes minimize storage overheads [Lin et al. 2004] and replication minimize communication overheads [Rodrigues and Liskov 2005].

In order to reduce communication overheads for erasure codes, Wu et al. [Wu et al. 2005] proposed the use of a hybrid scheme combining erasure codes and replication. Although this technique slightly increases the storage overhead, it can significantly reduce the communication overhead of erasure codes when node on-line availabilities are high. Another technique used to minimize the communication overhead consists in lazy redundancy maintenance [Kiran et al. 2004; Datta and Aberer 2006] which amortizes the costs of several consecutive repairs. However, deferring repairs can reduce the amount of available redundancy, requiring extra redundancy to guarantee the same data reliability. Furthermore, lazy repairs lead to spikes in the network resource usage [Duminuco et al. 2007; Sit et al. 2006].

New coding schemes such as Hierarchical Codes or tree structured data regeneration have also been proposed to reduce the communication overhead as compared to classical erasure codes [Li et al. 2010; Duminuco and Biertack 2008]. These solutions propose storage optimizations that exploit heterogeneities in node bandwidth and node availabilities. Finally, Dimakis et al. presented Regenerating Codes [Dimakis et al. 2007] as a flexible redundancy scheme for distributed storage systems. Regenerating Codes use ideas from network coding to define a new family of erasure codes that can achieve different trade-offs in the optimization of storage and communication costs. This flexibility allows to adjust the code to the underlying storage infrastructure. However, there are no studies on how Regenerating Codes should be adapted to these infrastructures, or how Regenerating Codes should be configured when combined with file replication in hybrid schemes. In this paper we will use Regenerating Codes [Dimakis et al. 2007, Dimakis et al. 2010] as the base of our analysis on how to adapt and optimize redundancy schemes for different underlying storage infrastructures and different application needs.
3. MODELING A GENERIC DISTRIBUTED STORAGE SYSTEM

We consider a storage system where nodes dynamically join and leave the system [Duminuco et al. 2007; Utard and Vernois 2004]. We assume that node lifetimes are random and follow some specific distribution \(L\). Because of these dynamics, the number of on-line nodes at time \(t\), \(N_t\), is a random process that fluctuates over time. Once stationarity is reached, we can replace \(N_t\) by its limiting version \(N = \lim_{t \to \infty} N_t\). Assuming that node arrivals follow a Poisson process with a constant rate \(\lambda\), then the average number of nodes in the system is \(N = \lambda \cdot E[L]\) [Pamies-Juarez and García-López 2010]. Additionally, it has been observed in real traces that during their lifetime in the system, nodes present several off-line periods caused by transient failures [Steiner et al. 2007; Guha et al. 2006]. To model these transient failures, we model each node as an alternating process between on-line and off-line states. The sojourn times at these states are random and follow two different distributions: \(X_{on}\) and \(X_{off}\) respectively. Using these distributions we can measure the node on-line availability in stationary state as [Yao et al. 2006]:

\[
a = \frac{E[X_{on}]}{E[X_{on}] + E[X_{off}]}.\]

All the \(N\) nodes in the system are responsible to store a constant amount of data that is uniformly distributed among the \(N\) nodes. To model different data granularity, we will consider that this total amount of stored data corresponds to \(O\) different data files of size \(M\) bytes. However, since each of these files is stored with redundancy, the total disk space required to store each file is \(R \cdot M\), being \(R\) the redundancy factor (or stretch factor). The value of \(R\) is set to guarantee that files are always available with a probability, \(p\), that is very close to one.

When a node reaches the end of its life, it abandons the system, losing all the data stored on it. A repair process is responsible to recreate the lost redundancy and to ensure that the retrieve probability, \(p\), is not compromised. There are three main approaches used to recreate redundancy when nodes fail:

1. **Eager repairs**: Lost redundancy is repaired on demand immediately after a node failure is detected.
2. **Lazy repairs**: The system waits until a certain number of nodes had failed and repairs them all at once.
3. **Proactive repairs**: The system schedules the insertion of new redundancy at a constant rate, which is set according to the average node failure rate.

In our storage model we will assume the use of proactive repairs. Compared to eager repairs, proactive repairs simplify the analysis of the communication costs. Furthermore, while lazy repair can reduce the maintenance costs by amortizing the communication costs across several repairs [Datta and Aberer 2006], it presents some important drawbacks: (i) delaying repairs leads to periods with low-redundancy that makes the system vulnerable; (ii) lazy repairs cause network resource usage to occur in bursts, creating spikes of system utilization [Duminuco et al. 2007]. By adapting a proactive repair strategy, communication overheads are evenly distributed in time and we can analyze the storage system in its steady state [Duminuco et al. 2007].

4. REGENERATING CODES

Regenerating Codes [Dimakis et al. 2007] are a family of erasure codes that allow to trade-off communication cost for storage cost and vice versa. To store a file of size \(M\) bytes, Regenerating Codes generate \(n\) blocks each to be stored on a different storage node. Each of these storage blocks has a size of \(\alpha\), which makes the file stretch factor \(R\) to be \(R = n\alpha / M\). When a storage node leaves the system or when a failure occurs, a new node can repair the lost block by downloading a repair block of size \(\beta\) bytes, \(\beta \leq \alpha\), from any set of \(d\) out of \(n - 1\) alive nodes \((k \leq d \leq n - 1)\). We will refer to \(d\) as the repair degree. The total amount of data received by the repairing node, \(\gamma, \gamma = d\beta\), is called the repair bandwidth. Finally, a node can reconstruct the file by downloading \(\alpha\) bytes.
Fig. 1. Scheme for the repair and retrieve operations of Regenerating Codes.

Dimakis et al. [Dimakis et al. 2007] gave the conditions that the set of parameters \((n, k, d, \alpha, \gamma = d\beta)\) must satisfy to construct a valid Regenerating Code. Basically, once the subset of parameters: \((n, k, d)\) is fixed, Dimakis et al. obtained an analytical expression for the relationship between the values of \(\alpha\) and \(\gamma\). This \(\alpha\)-\(\gamma\) relationship presents a trade-off curve: the larger \(\alpha\), the smaller \(\gamma\), and vice-versa. It means that it is impossible to simultaneously minimize both, communication cost and storage cost. Since the maximum storage capacity of the system can be constrained either by bandwidth bottlenecks or disk storage bottlenecks, there are two extreme \((\alpha, \gamma)\)-points of this trade-off curve that are of special interest w.r.t. maximizing the storage capacity. The first is the point where the storage block size \(\alpha\) per node is minimized, which is referred to as Minimum Storage Regenerating (MSR) code. The second is the point where the repair bandwidth \(\gamma\) is minimized, which is referred to as Minimum Bandwidth Regenerating (MBR) code. According to [Dimakis et al. 2010], the storage block size \((\alpha)\) and the repair bandwidth \((\gamma)\) for MSR and MBR codes are:

\[
(\alpha_{\text{MSR}}, \gamma_{\text{MSR}}) = \left( \frac{M}{k}, \frac{M}{k} \cdot \frac{d}{d-k+1} \right)
\]

\[
(\alpha_{\text{MBR}}, \gamma_{\text{MBR}}) = \left( \frac{M}{k} \cdot \frac{2d}{2d-k+1}, \frac{M}{k} \cdot \frac{2d}{2d-k+1} \right)
\]

There are two particular MSR configurations of special interest:

— Maximum-distance separable (MDS) codes: In MSR codes, when \(d = k\), we obtain \(\beta_{\text{MSR}} = \alpha_{\text{MSR}}\) and the Regenerating Code behaves exactly like a traditional MDS codes such as a Reed Solomon code [Reed and Solomon 1960]. In this case, the repair bandwidth, \(\gamma_{\text{MDS}} [k = d]\), is identical to the size of the original file, \(M\):

\[
\gamma_{\text{MDS}}[k = d] = d \beta_{\text{MSR}} = k \alpha_{\text{MSR}} = k \frac{M}{k} = M.
\]

— File replication: In MSR codes, when \(k = d = 1\), the code becomes a simple replication scheme where the \(n\) storage nodes each store a complete copy of the original file. For \(k = d = 1\), the...

(ending of text)
Table I. Symbols used.

| Symbol | Description |
|--------|-------------|
| \( N \) | Average number of storage nodes. |
| \( \lambda \) | Node arrival/departure rate (nodes/sec.). |
| \( L \) | Distribution of the node lifetime (sec.). |
| \( a \) | Node on-line availability. |
| \( O \) | Number of stored files. |
| \( M \) | Size of the stored files (bytes). |
| \( \omega \) | Service bandwidth of each node (KBps). |
| \( p \) | Data availability. Probability of detecting \( k \) blocks on-line. |
| \( n \) | Number of storage blocks. |
| \( k \) | Retrieval degree: number of blocks required for retrieval of original data. |
| \( d \) | Repair degree: number of blocks required for repair. |
| \( \alpha \) | Storage block size. |
| \( \beta \) | Repair block size. |
| \( \gamma \) | Repair bandwidth. |

Storage block size, \( \alpha_{\text{MSR}} [k = d = 1] \), and the repair bandwidth, \( \gamma_{\text{MSR}} [k = d = 1] \), are equal to the size of the original file, \( \alpha_{\text{MSR}} [k = d = 1] = \gamma_{\text{MSR}} [k = d = 1] = M \).

In Table I we summarize the symbols used throughout the paper.

5. COST ANALYSIS

5.1. Redundancy Cost

In Section 4 we defined data redundancy as \( R = n\alpha/M \). In this section we aim to measure the minimum \( R \) required to guarantee a desired file retrieve probability \( p \). Since in Regenerating Codes the retrieval process needs to download \( k \) different blocks out of the total \( n \) blocks, the retrieve probability \( p \) is measured as [Lin et al. 2004],

\[
p = \sum_{i=k}^{n} \binom{n}{i} a^i (1-a)^{n-i}.
\]  

(3)

Given the values of \( k \), \( a \) and \( p \), we can use eq. (3) to determine the minimum number of redundant blocks required to guarantee a certain retrieve probability \( p \) using the function \( \eta \):

\[
\eta[k,a,p] = \min \left\{ \eta' : p \leq \sum_{i=k}^{\eta'} \binom{n'}{i} a^i (1-a)^{n'-i}, \eta' \geq k \right\}.
\]

(4)

Note that the number of redundant blocks required to achieve \( p \) is a function of the repair degree, \( k \), the node on-line availability, \( a \), and \( p \). In the rest of this paper we will use the notation \( \eta[k,a,p] \) to refer to the number of storage blocks \( n \) required to achieve a retrieve probability \( p \) for the specific \( k \) and \( a \) values.

Since data redundancy is \( R = n\alpha/M \), we can obtain the redundancy required by MSR and MBR codes, \( R_{\text{MSR}} \) and \( R_{\text{MBR}} \) respectively, by substituting \( \alpha \) with the expressions given for \( \alpha \) in eq. (1) and eq. (2):

\[
R_{\text{MSR}} = \frac{\eta[k,a,p] \cdot \alpha_{\text{MSR}}}{M} = \frac{\eta[k,a,p] \cdot (M/k)}{M} = \frac{\eta[k,a,p]}{k}
\]

(5)

\[
R_{\text{MBR}} = \frac{\eta[k,a,p] \cdot \alpha_{\text{MBR}}}{M} = \frac{\eta[k,a,p] \cdot (2dM/(k(2d-k+1)))}{M} = \frac{2d \cdot \eta[k,a,p]}{k(2d-k+1)}
\]

(6)

Using these expressions we can state the following lemma:

**Lemma 5.1.** For \( n \), \( k \) and \( d \) fixed, the redundancy \( R_{\text{MSR}} \) required by MSR codes is always smaller than or equal to the redundancy \( R_{\text{MBR}} \) required by MBR codes.
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(a) Redundancy for MSR codes (includes MDS codes).

(b) Redundancy for MBR codes.

(c) Value of \( \eta[k, a, p] \).

Fig. 2. Redundancy \( R \) required to achieve a retrieve probability \( p = 0.999999 \) for MSR and MBR codes as a function of the retrieve degree \( k \). Each plot in (a) and (b) depicts the redundancy evaluated using eq. (5) and eq. (6) for different values of \( d \), and different values of the node on-line availability \( a \). In (c) we plot the number of storage blocks \( n \) required to achieve the retrieve probability \( p \) for each case.

**Proof.** We can state the lemma as \( R_{MSR} \leq R_{MBR} \). Using equations (5) and (6) we obtain:

\[
\frac{\eta[k, a, p]}{M} \cdot \alpha_{MSR} \leq \frac{\eta[k, a, p]}{M} \cdot \alpha_{MBR}
\]

which is true by the definition of MSR codes and MBR codes [Dimakis et al. 2007].

In Figure 2a and 2b we plot the redundancy \( R \) required to achieve a retrieve probability \( p = 0.999999 \) for MSR and MBR codes. We plot the values of \( R \) as a function of the retrieve degree \( k \), and for different node availabilities, \( a \). Additionally, for MBR codes we also depict the values of \( R_{MBR} \) for the two extreme repair degree values: \( d = k \) and \( d = n - 1 \). We do not evaluate \( R_{MSR} \) for different \( d \) values because \( R_{MSR} \) is independent of \( d \) (see eq. (5)). In Figure 2c we use eq. (3) to plot the number of blocks, \( \eta[k, a, p] \), used in figures 2a and 2b for the retrieve probability \( p = 0.999999 \).

In Figure 2a we can see that for MSR and MBR, increasing \( k \) reduces \( R \), and therefore, reduces storage costs. Additionally, comparing figures 2a and 2b we can appreciate the consequences of Lemma 5.1 for a given node availability, \( a \), and a retrieve degree \( k \), the redundancy required for MSR codes is always smaller than the redundancy required for MBR codes. Finally, we can see that \( R \) first quickly decreases with increasing \( k \) before it reaches its asymptotic values. There is no point in choosing \( k \) very large to minimize the storage costs of MSR and MBR codes, since large \( k \) values induce a very high computational cost for coding and decoding [Dimunico and Biersack 2009]. We therefore recommend to use values for \( k \) where the redundancy \( R \) starts approaching the asymptote, namely \( k = 5 \) for \( a = 0.99 \), \( k = 20 \) for \( a = 0.75 \) and \( k = 50 \) for \( a = 0.5 \). In Table II we provide the redundancy savings achieved by using these \( k \) values.
Table II. Storage space savings for adopting a Regenerating Code instead of replication. We use different $k$ values for each on-line node availability and a target retrieve probability of $p = 0.999999$.

|       | $a = 0.5$ | $a = 0.75$ | $a = 0.99$ |
|-------|-----------|-----------|-----------|
| MSR   | 47%       | 77%       | 84%       |
| MBR ($d = k$) | 69%       | 55%       | 11%       |
| MBR ($d = n - 1$) | 81%       | 70%       | 25%       |

5.2. Communication Costs

When a node fails, the system must repair all the data blocks stored on the failed node. Repairing each of these blocks requires to transfer data between nodes, which entails a communication cost. In this section we measure the minimum per-node bandwidth required to sustain the overall repair traffic of the storage system. We will first compute the total amount of data that is transferred within the system during a period of time $\Delta$:

$$\text{data transferred during } \Delta = \text{ nodes failed during } \Delta \times \text{ blocks stored per node } \times \frac{\eta}{\text{traffic to repair one block}}. \quad (7)$$

Assuming that there are $N$ nodes with an average lifetime $\mathbb{E}[L]$, the average number of nodes that fail during a period $\Delta$ is $\Delta N/\mathbb{E}[L]$ [Duminuco et al., 2007]. Additionally, assuming that data blocks are uniformly distributed between all storage nodes, the average number of blocks stored per node is $n \cdot O/N$. Finally, since the traffic required to repair one failed block is $\gamma$, we can rewrite eq. (7) as:

$$\text{data transferred during } \Delta = \left(\Delta \frac{N}{\mathbb{E}[L]}\right) \times \left(\frac{n O}{N}\right) \times \gamma \quad (8)$$

Then, the minimum per-node bandwidth, $W$, required to ensure that all stored data can be successfully repaired is the ratio between the amount of data transmitted per unit of time (in seconds), and the average number of on-line nodes, $aN$:

$$W = \frac{\text{data transferred during } \Delta}{\Delta \times \text{ avg. number on-line nodes}} = \frac{\gamma n O}{a N \mathbb{E}[L]}. \quad (9)$$

Assuming that the repair bandwidth, $\gamma$, is given in KB, and the node lifetime, $L$, in seconds, then the minimum per-node bandwidth $W$ is expressed in KBps. Assuming that the upload bandwidth of each node is always smaller than or equal to the download bandwidth, this minimum per-node bandwidth, $W$, represents the minimum upload bandwidth required by each node.

If we use the values of the repair bandwidth $\gamma$ given in equations (1) and (2), we obtain the minimum per-node bandwidth for each Regenerating Code configuration:

$$W_{\text{MSR}} = \gamma_{\text{MSR}} \cdot \frac{\eta[k, a, p]}{a N \mathbb{E}[L]} = \frac{\mathcal{M}}{k} \frac{d}{(d-k+1)} \frac{\eta[k, a, p]}{a N \mathbb{E}[L]} = \frac{d \cdot \eta[k, a, p]}{ak(d-k+1) N \mathbb{E}[L]} \quad (10)$$

$$W_{\text{MBR}} = \gamma_{\text{MBR}} \cdot \frac{\eta[k, a, p]}{a N \mathbb{E}[L]} = \frac{\mathcal{M}}{k} \frac{2d}{(2d-k+1)} \frac{\eta[k, a, p]}{a N \mathbb{E}[L]} = \frac{2d \cdot \eta[k, a, p]}{ak(2d-k+1) N \mathbb{E}[L]} \quad (11)$$

Taking these two expressions we can state the following lemma:

**Lemma 5.2.** For the same $n$, $k$ and $d$ parameters, the per-node bandwidth required by MBR codes, $W_{\text{MBR}}$, is always smaller than or equal to the per-node bandwidth required by MSR codes, $W_{\text{MSR}}$. 

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Fig. 3. We use eq. (10) to show the per-node bandwidth required to achieve $p = 0.999999$ for MSR codes.

**PROOF.** We can state the lemma as $W_{\text{MBR}} \leq W_{\text{MSR}}$. Using equations (10) and (11) we obtain:

$$\gamma_{\text{MBR}} \cdot \frac{\eta[k, a, p]}{a N E[L]} \leq \gamma_{\text{MSR}} \cdot \frac{\eta[k, a, p]}{a N E[L]}$$

which is true by the definition of MSR codes and MBR codes from [Dimakis et al. 2007].

In the rest of this section we analyze the per-node bandwidth requirements, $W$, for MSR and MBR codes. Since in eq. (10) and eq. (11) the term $\frac{OM}{NE[L]}$ does not depend on the Regenerating Code parameters, $n, k, d$, we will assume that $\frac{OM}{NE[L]} = 1$. To obtain the minimum per-node bandwidth, we simply have to multiply $W$ times $\frac{OM}{NE[L]}$.

**Communication Cost for MSR Codes.** In Figure 3 we use eq. (10) to analyze the per-node bandwidth requirements of MSR codes when the required retrieve probability is $p = 0.999999$. We plot the results for $d = k$ and $d = n - 1$ and for three different on-line node availabilities:

— For $d = k$ we can see in Figure 3a how the per-node bandwidth of a MDS code such as a Reed-Solomon code, is linear in $k$. In this case, the lowest per-node bandwidth is achieved when $k = 1$, which corresponds to a simple replication scheme.

— For $d = n - 1$, however, we can see in Figure 3b that the per-node bandwidth is asymptotically decreasing in $k$. However, as already said, we recommend to choose $k = 20$ when $a = 0.75$ and $k = 50$ when $a = 0.5$. Finally, we can see that for $a = 0.99$, $W_{\text{MBR}}$ is not an asymptotically decreasing function: As $a$ tends to one, the number of required blocks, $\eta[k, a, p]$, tends to $k$ (see eq. (4)) and the case $d = n - 1$ is identical to the case $d = k$, which is depicted in sub-figure 3a.

In Figure 3a we saw that MDS codes ($d = k; k > 1$) do not reduce the per-node bandwidth as compared to replication ($d = k = 1$) while in Figure 3b we saw that for $d > k$, a MSR code can reduce the bandwidth as compared to replication except for high node on-line availabilities ($a = 0.99$). We now want to determine the maximum node on-line availability, $a$, for which a MSR code can reduce the per-node bandwidth requirement as compared to replication. Let us denote by $W_{\text{MSR}}[k = d = 1]$ the per-node bandwidth required by replication and $W_{\text{MSR}}[k > 1, d \geq k]$ denote the per-node bandwidth required by a MSR code. Then, a MSR reduces the bandwidth required by replication when the following inequality holds:

$$W_{\text{MSR}}[k = d = 1] \geq W_{\text{MSR}}[k > 1, d \geq k] \quad (12)$$

Table III shows the minimum $d$ that satisfies the inequality defined in eq. (12) for different on-line node availabilities, $a$, and different retrieve degrees $k$. We additionally provide the number of storage blocks, $n$, required to achieve $p = 0.999999$. We can see that for low node availabilities
Table III. Minimum \(d\) values to construct MSR codes that requiring less repair bandwidth than simple file replication. The target retrieve probability is \(p = 0.999999\).

| Node availability | minimum repair degree satisfying eq. (12) and the value of \(n\). |
|-------------------|---------------------------------------------------------------|
| \(a = 0.5\)       | \(k = 50; d = 59\)                                           |
| \(a = 0.75\)      | \(k = 29; d = 47\)                                           |
| \(a = 0.9\)       | \(k = 5; d = 13\)                                            |
| \(a = 0.92\)      | \(k = 20; d = 12\)                                           |
| \(a = 0.95\)      | \(k = 5; d = 8\)                                             |
| \(a = 0.99\)      | \(k = 5; d = 8\)                                             |

Fig. 4. Per-node bandwidth required to achieve \(p = 0.999999\) for MBR codes using eq. (9).

Communication Cost for MBR Codes. In Figure 4 we plot the required per-node bandwidth of MBR codes for \(d = k\) and \(d = n - 1\). For MBR codes, in difference to MSR codes, we can see that for both \(d\) values the required per-node bandwidth \(W\) asymptotically decreases with increasing \(k\) and we can state:

**Remark 5.3.** For MBR codes \(W_{MBR} [k = k'] \geq W_{MBR} [k = k' + 1]\).

From Lemma 5.2 we know that for the same configuration, MBR codes are more bandwidth efficient than MSR codes. Using Remark 5.3 we can now state that all MBR codes are also more bandwidth efficient than simple replication, which is a special case of MSR:

**Lemma 5.4.** The per-node bandwidth requirements of MBR codes are lower than or equal to the per-node bandwidth requirements of simple replication: \(W_{MBR} \leq W_{MSR} [k = d = 1]\).

**Proof.** If this lemma is true, then the per-node bandwidth of the MBR configuration that consumes the most bandwidth must be lower than or equal to the per-node bandwidth of replication. Since \(W_{MBR}\) is largest for \(k = 1\) (see Remark 5.3), we can rewrite this lemma as: \(W_{MBR} [k = d = 1] \leq W_{MSR} [k = d = 1]\). To proof it by contradiction we assume that

small values of \(d\), slightly larger than \(k\), are sufficient to reduce the per-node bandwidth required by replication. However, for high on-line node availabilities, the minimum value of \(d\) satisfying eq. (12) becomes larger than \(n - 1\), which is not a valid Regenerating Code configuration. This maximum on-line availability becomes higher for low \(k\) values, namely \(a \geq 0.95\) for \(k = 50\), \(a \geq 0.97\) for \(k = 20\) and \(a \geq 0.99\) for \(k = 5\). We can generally state that for high on-line node availabilities, replication becomes more bandwidth efficient than any MSR code, which confirms the result obtained by Rodrigues and Liskov in [Rodrigues and Liskov 2005].
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Fig. 5. Reduction of the communication cost by adopting a MBR code instead of replication as function of $k$ a retrieve probability of $p = 0.999999$.

$$W_{\text{MBR}}[k = 1] > W_{\text{MSR}}[k = d = 1].$$

Using equations (10) and (11) we obtain:

$$\gamma_{\text{MBR}}[k = d = 1] \cdot \frac{\eta[1,a,p]}{\alpha N E[L]} > \gamma_{\text{MSR}}[k = d = 1] \cdot \frac{\eta[1,a,p]}{\alpha N E[L]}$$

$$\gamma_{\text{MBR}}[k = d = 1] > \gamma_{\text{MSR}}[k = d = 1]$$

which is a contradiction. \( \square \)

In Figure 5 we plot the communication savings a storage system makes when using a MBR code instead of replication. The savings have the same asymptotic behavior than the bandwidth requirements, $W_{\text{MBR}}$, depicted in Figure 4. Since for MBR codes $\alpha_{\text{MBR}} = \gamma_{\text{MBR}}$, i.e. the storage block size is the same as the repair bandwidth, the communication savings for MBR are the same as the storage savings listed in Table II.

6. HYBRID REPOSITORIES

In Section 5 we saw that except for one a particular case (MSR codes and high node on-line availabilities), MSR and MBR codes offer both, lower storage costs and lower communication costs than simple file replication. However, there are some scenarios where the storage system needs to ensure that files can be accessed without the need of decoding operations. For example, storage infrastructures using replication [Ghemawat et al. 2003; Borthakur 2007] may not afford a migration of their infrastructures from replication to erasure encodes. Other examples are on-line streaming services or content distribution networks (CDNs) that need efficient access to stored files without requiring complex decoding operations.

As we saw in Section 5, maintaining whole file replicas (MSR codes with $k = d = 1$) has a higher storage cost than using coding schemes. However, when whole file replicas are required, storage systems can reduce this high cost by using a hybrid redundancy scheme that combines replication and erasure codes. The replicas can also help reduce the communication cost when repairing lost data by generating new redundant blocks using the on-line file replicas: Generating a redundant block from a file replica requires transmitting $\alpha$ bytes instead of the $\gamma = d \cdot \beta$ bytes required by the normal repair process. From eqs. (1) and (2) it is easy to see that $\alpha \leq \gamma$. While some papers have studied hybrid redundancy schemes [Rodrigues and Liskov 2005; Hauberlen et al. 2005; Dimakis et al. 2007], their aim was to reduce communication costs and not to guarantee permanent access to replicated objects. Therefore, these papers assumed that only one replica of each file was maintained in the system, ignoring the two problems that arise when this replica goes temporarily off-line: (i) it is not possible to access the file without decoding operations, and (ii) repairs using the replica are not possible.
In this section we evaluate a different hybrid scenario, where the storage system may maintain more than one replica of the whole file in order to ensure with high probability that there is always one replica on-line. However, it is not clear if the overall communication costs of our hybrid scheme will be lower than the communication costs of a single replication scheme. Further, even if communication costs are reduced, the use of a double redundancy scheme (replication and coding) may increase storage costs. To the best of our knowledge, there is no prior work analyzing these aspects.

In our analysis we differentiate between the probability $p_{\text{low}}$ of having a file replica on-line, and the retrieve probability $p$ for being able to retrieve a file using encoded blocks, which requires that $k$ out of a total of $n$ storage blocks are on-line. We assume that $p_{\text{low}} \ll p$, for example $p_{\text{low}} = 0.99$ and $p = 0.999999$, which is motivated by the fact that while users are likely to tolerate higher access times to a file, which will need to be reconstructed first in some rare cases when no replicas are found on-line, but they require very strong guarantees that data is never lost.

Adapting Communication Cost to the Hybrid Scheme. In a hybrid scheme we need to consider two types of repair traffic, namely (i) traffic $W_{\text{MSR}}[k = d = 1]$ to repair lost replicas and (ii) traffic $W_{\text{repl}}$ to repair encoded blocks. Since in the hybrid scheme blocks are repaired directly from a replicated copy, repairing an encoded block requires transmitting only one new storage block of $\alpha$ bytes. We obtain $W_{\text{repl}}$ by replacing in eq. (7) the term “traffic to repair a block” in by $\alpha$. Arranging the terms we obtain the following two expressions:

$$W_{\text{repl}} = \frac{\eta[k, a, p]}{ka} \times \frac{MO}{N \mathbb{E}[L]}$$  \hspace{1cm} (13)

$$W_{\text{repl}} = \frac{2d \cdot \eta[k, a, p]}{ka(2d - k + 1)} \times \frac{MO}{N \mathbb{E}[L]}$$  \hspace{1cm} (14)

Note that these expressions assume that all lost blocks are repaired from replicas. Since we are adopting a proactive repair scheme, the system can delay individual repairs when no replicas are available. However, since replicas are available most of the time, these delays will rarely happen.

Comparing $W_{\text{repl}}^{\text{MSR}}$ and $W_{\text{repl}}^{\text{MBR}}$ we can state the following lemma:

**Lemma 6.1.** For the same $k$, $d$ and $p$ parameters, a hybrid scheme using a MBR code has a communication cost that is at least as high as the communication cost of a hybrid scheme using a MSR code.

**Proof.** We can state the lemma as $W_{\text{repl}}^{\text{MSR}} \leq W_{\text{repl}}^{\text{MBR}}$. Using equations (13) and (14) we obtain:

$$\frac{\eta[k, a, p]}{ka} \times \frac{MO}{N \mathbb{E}[L]} \leq \frac{2d \cdot \eta[k, a, p]}{ka(2d - k + 1)} \times \frac{MO}{N \mathbb{E}[L]}$$

$$1 \leq \frac{2d}{2d - k + 1}$$

$$1 \leq k$$

which is true by the definition of Regenerating Codes.

Lemma 6.1 implies that MSR codes when used in hybrid schemes are both, more storage-efficient and more bandwidth-efficient than MBR codes. For this reason we will not consider the use of MBR codes in hybrid schemes.

Let us assume that the required retrieve probability for the whole hybrid system is $p$ and that the retrieve probability for replicated objects is $p_{\text{low}}$, $p_{\text{low}} \ll p$. A hybrid scheme reduces the storage cost compared to replication when the following condition is satisfied:

$$R_{\text{MSR}}[k = 1; p_{\text{low}}] + R_{\text{MSR}}[k > 1; p] < R_{\text{MSR}}[k = 1; p] .$$  \hspace{1cm} (15)

Where $R_{\text{MSR}}[k = 1; p]$ represents hybrid storage costs and $R_{\text{MSR}}[k > 1; p]$ represents replication storage costs.
Table IV. Number of replicas required to achieve a retrieve probability \( p_{\text{low}} \) for different node availabilities \( a \).

| Node availability \( a \) | \( P_{\text{low}} = 0.99 \) | \( P_{\text{low}} = 0.98 \) | \( P_{\text{low}} = 0.95 \) |
|---------------------------|---------------------|---------------------|---------------------|
| 0.5                       | 7                   | 6                   | 5                   |
| 0.75                      | 4                   | 3                   | 3                   |
| 0.99                      | 1                   | 1                   | 1                   |

And analogously, a hybrid scheme reduces communication costs when:

\[
W_{\text{MSR}}[k = 1; P_{\text{low}}] + W_{\text{rep}}^{\text{MSR}}[k > 1; p] < W_{\text{MSR}}[k = 1; p].
\]  
(16)

In Figure 6, the \((p, p_{\text{low}})\)-pairs under each of the lines represent the scenarios where a hybrid scheme (replication+MSR codes) reduces the costs of a single replicated scheme. The lines are the maximum \( p_{\text{low}} \) values that satisfy eq. (15) for (a), and eq. (16) for (b) and (c).

As example, let us assume a storage system that wants 99% data availability for their replicated files. In this case \((p_{\text{low}} = 0.99)\), looking at Figure 6 we see that a hybrid scheme (replication+MSR codes) can reduce the storage costs compared to replication only when \( p \geq 0.999999 \) for \( a = 0.99 \), when \( p \geq 0.99 \) for \( a = 0.75 \), and when \( p \geq 0.9 \) for \( a = 0.5 \). Since in general we always want strong guarantees that files are never lost — e.g., we assume \( p \geq 0.999999 \) —, we can conclude that hybrid schemes reduce storage and communication cost for almost all practical scenarios.

It is interesting to note that in Figure 6, all three sub-figures look very much alike. The reason is that the cost contribution of replication is significantly higher than the cost contribution of the coding (see Section 5). Since we have demonstrated the cost efficiency of a hybrid scheme for \( p_{\text{low}} = 0.99 \), which requires a larger number of replicas than configurations with \( p_{\text{low}} \leq 0.99 \), see Table IV, a hybrid scheme will also reduce storage and communication costs for any system requiring fewer replicas i.e., \( p_{\text{low}} \leq 0.99 \).
how the network traffic caused by repair processes can affect the performance and scalability of the redundancy scheme. For that, we assume a distributed storage system constrained by its network bandwidth: a system where storage nodes have low upload bandwidth and nodes have low on-line availabilities. For such a storage system we will evaluate two measures that are difficult to obtain analytically: (i) the real bandwidth used by the repair process —i.e., bandwidth utilization—, and (ii) the repair time —i.e., time required to download \( d \) fragments. In this way we can evaluate the impact of the repair degree \( d \) on bandwidth utilization and system scalability.

**Bandwidth utilization.** Given a node upload bandwidth, \( \omega \), and the per-node required bandwidth, \( W \), we can theoretically state that a feasible storage system must satisfy \( \omega \geq W \), and that the storage system reaches its maximum capacity when \( \omega = W \). However, practical storage systems may not reach this maximum capacity because of system inefficiencies due to failed repairs or fragment retransmissions. To measure these inefficiencies, we will compare the real bandwidth utilization \( \hat{\rho} \) with the theoretical bandwidth utilization \( \rho = W/\omega \).

**Repair time.** The repair time is proportional to the repair bandwidth, \( \gamma \), the repair degree, \( d \), and the probability \( a \) of finding a node on-line [Pamies-Juarez et al. 2010]. We showed in Section 5 that increasing \( d \) reduces the repair bandwidth \( \gamma \) (see eqs. 11 and 12), which should then intuitively reduce repair times. However, since the system only guarantees \( k \) on-line nodes, contacting \( d > k \) nodes may require to wait for nodes coming back on-line, which will cause longer repair times. In previous sections we only considered two repair degrees \( d \), namely \( d = k \) and \( d = n - 1 \). In this section we will analyze how different \( d \) values affect repair times and bandwidth utilization.

### 7.1. Simulator Set-Up

We implemented an event-based simulator that simulates a dynamic storage infrastructure. Initially, the simulator starts with \( N = 500 \) storage nodes. New node arrivals follow a Poisson process with average inter-arrival times \( E[L]/N \). Node departures follow a Poisson process with the same inter-departure time. Once a node joins the system it draws its lifetime from an exponential distribution \( L \) with expected value \( E[L] = 100 \) days. During their lifetime in the system, nodes alternate between on-line/off-line sessions. For each session, each node draws its on-line and off-line durations from distributions \( X_{\text{on}} \) and \( X_{\text{off}} \) respectively. In this paper \( X_{\text{on}} \) and \( X_{\text{off}} \) are exponential variates with parameters \( 1/(B \cdot a) \) and \( 1/(B(1 - a)) \) respectively, where \( B \) is the base time and \( a \) the node on-line availability. Using the mean value of the exponential distribution we can compute the average duration of the on-line and off-line periods as (in hours):

\[
E[X_{\text{on}}] = B \cdot a \tag{17}
\]

\[
E[X_{\text{off}}] = B \cdot (1 - a) \tag{18}
\]

The simulator implements parameterized Regenerating Code. To cope with node failures, redundant blocks are repaired in a proactive manner following the algorithm defined in [Duminuco et al. 2007] and the simulator proactively generates new redundant blocks at a constant rate. For each stored object, a new redundant block is generated every \( E[L]/n \) days. To balance the amount of data assigned to each node, each repair is assigned to the on-line node that is least loaded in terms of the number of stored blocks and the number of repairs going on.

If the repair node disconnects during a repair process, the repair is aborted and restarted at another on-line node. Similarly, when a node uploading data disconnects, the partially uploaded data is discarded and the repair node starts a block retrieval from another on-line node.

The number of objects stored in the system is set in all the simulations to achieve a desired system utilization \( \rho \). Given \( \rho \), the number of stored objects, \( O \), is obtained using the two following
Fig. 7. Bandwidth utilization and repair times for MSR and MBR and different repair degrees $d$ when the object size is $M=120$MB and the number of objects $O$ is set to achieve half bandwidth utilization $\rho = 0.5$. The rest of the parameters are set to: $k=20$ and $B=24$ hours.

These formulas are obtained by taking the definition of utilization, $\rho = W/\omega$, replacing $W$ by $\rho \cdot \omega$ in eq. (9) and solving the equation for $O$.

We set the on-line node availability to $a = 0.75$ and we set $k = 20$. With these values, we use eq. (4) to compute the minimum number of redundant blocks, $n$, required to achieve a retrieve probability $p = 0.999999$: $\eta[20, 0.75, 0.999999] = 47$.

Finally, the node upload bandwidth is set to $\omega = 20$KB/sec, allowing only one concurrent upload per node. To simulate asymmetric network bandwidth, we allow up to 3 concurrent downloads per node, which makes a maximum download bandwidth of 60KB/sec.

7.2. Impact of the Repair Degree $d$

In Figure 7 we measure the effect of the repair degree on the system utilization and on the repair times. In this experiment, we set the size of the object to $M=120$MB and the base time to $B=24$ hours —i.e. on average nodes connect and disconnect once per day. The number of stored objects is set to achieve a bandwidth utilization of $\rho = 0.5$. Figure 7c shows the number of objects $O$ for $\rho = 0.5$, and Figure 7d the storage space required. Figures 7a and 7b show that small $d$ values (values close to $k = 20$) allow to keep the bandwidth utilization on target and assure low repair times. However, for repair degrees $d > 34$ the repair times start to increase exponentially.
It is interesting to see that when the repair times are quite long, nodes executing repairs may not finish their repairs before disconnecting since repair times become longer than on-line sessions. In this case, failed repairs are reallocated and restarted in other on-line nodes. These unsuccessful repairs cause useless traffic that increase then the real bandwidth utilization. In Figure 7a we can see how for $d > 38$ repair times start to be larger than on-line sessions, increasing utilization beyond 0.5. It is important to note that these larger repair times can jeopardize the reliability of the system: large $d$ values can cause most repairs to fail, reducing the amount of available blocks and reducing the probability of successfully accessing stored files.

To investigate the increase of bandwidth utilization in detail, we analyze in Figure 8 the performance of the storage system for the point where repair times begin to increase, $d = 36$. At this point we evaluate repair times and bandwidth utilization for different base times, $B$. As $B$ increases, the duration of on-line sessions become longer and fewer repairs need to be restarted, theoretically reducing bandwidth utilization. We can see this effect in Figure 8a, larger base times reduce the bandwidth utilization of the system. Due to this utilization reduction, repair times are also slightly reduced as we can see in Figure 8b.

### 7.3. Scalability

Other than the impact of the repair degree $d$ and the base time $B$ we aim to analyze the behavior of the storage system under different target bandwidth utilizations. In Figure 9 we plot the measured utilization and repair times for a wide range of target utilizations $\rho$. We set the size of the stored objects to 120MB and we increase the number of stored objects, $O$, to achieve different utilizations. In this scenario we set $k = d = 20$. In Figure 9a, we see how the measured utilization is nearly the same than the target utilization. This is because $d = k$ causes short repair times and repairs typically finish before nodes go off-line. However, in Figure 9b, we can appreciate how for a high bandwidth utilization of $\rho = 0.9$, the saturation of the node upload queues increases repair times significantly.

In Figure 10 we plot the same metrics as in Figure 9 but for a repair degree of $d = 36$. Increasing the repair degree causes longer retrieval times, however as we saw in Figure 7, $d = 36$ keep repairs short enough to guarantee that the utilization is not affected. However, by increasing the repair degree from $d = 20$ to $d = 36$ we can store on the same system configuration one order of magnitude more objects, namely 6452 (MSR, $d = 36$) instead of 683 (MSR, $d = 20$).

Finally, in Figure 11 we analyze the impact of object size on bandwidth utilization and repair times. For each object size we set the number of stored objects to achieve a target bandwidth utilization of $\rho = 0.5$. Since the utilization is the same for all object sizes, the number stored objects, $O$, decreases as the object size increases (Figure 11). Independently of the object size, the total amount of stored data, $O \times M$ remains constant: 774GB for MSR codes and 1206GB for MBR.
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Fig. 9. Bandwidth utilization and repair times for MSR and MBR and different targeted utilizations $\rho$ when the object size is $M = 120$ MB and the number of objects $O$ is set to achieve the targeted $\rho$. The rest of the parameters are set to: $k = 20$, $B = 24$ hours and $d = 20$.

codes. We can also see in Figure 11a that the measured bandwidth utilization is independent of the object size. However, as expected, we can see in Figure 11b that larger objects take longer to repair.

8. CONCLUSIONS

In this paper we evaluated redundancy schemes for distributed storage systems in order to have a clearer understanding of the cost trade-offs in distributed storage systems. Specifically, we analyzed the performance of the generic family of erasure codes called Regenerating Codes [Dimakis et al. 2007], and the use of Regenerating Codes in hybrid redundancy schemes. For each parameter combination we analytically derived its storage and communication costs of Regenerating Codes. Our cost analysis is novel in that it takes into account the effects of on-line node availabilities and node lifetimes. Additionally, we used an event-based simulator to evaluate the effects of network utilization on the scalability of different redundancy configurations. Our main results are as follows:

— Compared to simple replication, the use of a Regenerating Codes can reduce the costs of a storage system (storage and communication costs) from 20% up to 80%.
— The optimal value of the retrieval degree $k$ depends on the on-line node availability, ranging from $k = 5$ when nodes have 99% availability, to $k = 50$ when nodes have 50% availability. Once $k$ is fixed, storage systems with limited storage capacity can maximize their storage capacity by adopting MSR codes. On the other hand, systems with limited communications bandwidth can maximize their storage capacity by adopting MBR codes.
— High repair degrees $d$ reduce the overall communication costs but may increase repair times significantly, which can lead to data loss. We experimentally found that the repair degree should be small enough to make sure the repair times are shorter than the on-line session durations of nodes.
Fig. 10. Bandwidth utilization and repair times for MSR and MBR and different targeted utilizations $\rho$ when the object size is $M = 120$MB and the number of objects $O$ is set to achieve the targeted $\rho$. The rest of the parameters are set to: $k = 20$, $B = 24$ hours and $d = 36$.

— Finally, in storage systems where the access to whole file replicas is required, we showed that hybrid schemes combining replication and MSR codes are more cost efficient than simple replication.

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