ABSTRACT
Classical erasure codes, e.g. Reed-Solomon codes, have been acknowledged as an efficient alternative to plain replication to reduce the storage overhead in reliable distributed storage systems. Yet, such codes experience high overhead during the maintenance process. In this paper we propose a novel erasure-coded framework especially tailored for networked storage systems. Our approach relies on the use of random codes coupled with a clustered placement strategy, enabling the maintenance of a failed machine at the granularity of multiple files. Our repair protocol leverages network coding techniques to reduce by half the amount of data transferred during maintenance, as several files can be repaired simultaneously. This approach, as formally proven and demonstrated by our evaluation on a public experimental testbed, enables to dramatically decrease the bandwidth overhead during the maintenance process, as well as the time to repair a failure. In addition, the implementation is made as simple as possible, aiming at a deployment into practical systems.

1. INTRODUCTION
Redundancy is key to provide a reliable service in practical systems composed of unreliable components. Typically distributed storage systems heavily rely on redundancy to mask ineluctable disk/node unavailabilities and failures. While three-way replication (often called triplication) is the standard means to obtain reliability with redundancy, it is now acknowledged that erasure codes can dramatically improve the storage efficiency [32]. In other words, for a given reliability guarantee, the storage overhead for such codes is reduced by order of magnitude compared to replication. Several major cloud systems as those of Microsoft [4] or Google [13] have recently adopted erasure codes (more specifically Reed-Solomon codes). Facebook was experimenting them in 2010 [30]. There is thus a tangible move of cloud operators from replication to erasure coding, allowing a more efficient use of scalability-critical resources.

Reed-Solomon codes are the de facto standard of code-based redundancy in practice. Yet, those codes have been designed and optimized to deal with lossy communication channels, rather than specifically targeting networked storage systems. In fact those codes only provide tolerance to transient failures, the level of redundancy irrevocably decreasing with host-node failures over time. An additional maintenance mechanism is thus key to preserve the reliability of stored information over time, as far as it is well known that storage systems have grown to a scale where failures have become the norm. However, Reed-Solomon codes are precisely known to suffer from important overhead in terms of bandwidth utilization and decoding operations when maintenance has to be triggered. In order to address these two drawbacks, architectural solutions have been proposed [26], as well as new code designs [11, 19, 20], paving the way for better tradeoffs between storage, reliability and maintenance efficiency. The optimal tradeoff has been very recently provided by Dimakis & al [7] with the use of network coding. However open issues regarding the feasibility of deploying those new codes in practical distributed storage systems remain. Indeed, very few studies evaluate how hard it is to implement theses codes in a production system [10], as most of them are theoretical. Moreover those new codes are examined under the simplifying assumption that only one file is stored per failed machine, thus ignoring practical issues when dealing with the maintenance of multiple files.

Interestingly enough, an appealing alternative for performance is to use randomness. Randomness can provide a simple and efficient way to construct optimal codes w.h.p., as are Reed-Solomon ones, while offering suitable properties in terms of maintenance. Random Codes have been identified as good candidates to provide fault tolerance in distributed storage systems [18, 15, 23]. Yet, maintaining such promising codes has not been considered in practice so far. In this paper we propose a novel approach to redundancy management, combining both random codes and network coding, to provide an efficient maintenance protocol usable in practice. The main intuition behind our approach is to apply random codes and network coding at the granularity of clusters hosting, enabling to factorize the repair cost across several files at the same time. This mechanism is made as simple as possible, both in terms of design and implementation with the purpose of leveraging the power of erasure codes, while reducing its known drawbacks.
More specifically, our contributions are the following:

1. We propose a novel maintenance mechanism which combines a clustered placement strategy, random codes and network coding techniques at the node level (i.e., between different files hosted by a single machine). This approach is called CNC in the sequel, for Clustered Network Coding. CNC enables to halve the data transferred compared to standard erasure codes during the maintenance process. The overhead in terms of decoding operations is also reduced by order of magnitude compared to the reparation process of classical erasure codes. Moreover, CNC enables reintegration (i.e., the capability to reintegrate nodes which have been wrongly declared as failed). Finally the network load is evenly balanced between nodes during the maintenance process, using a simple random selection. This enables the storage system to scale with the number of files to repair, as the available bandwidth is consumed as efficiently as it could be. Performance claims of CNC are formally proven.

2. We deployed CNC on a public execution platform, namely Grid5000 [1] to evaluate its benefits. In the typical setup of a datacenter storage system, data transferred, storage needs and repair time have been monitored. We compared our solution to both triplication and Reed-Solomon codes. Experimental results show that the data transferred for maintenance is reduced by half compared to codes while consuming the same storage space and providing the same data availability. The combination of the data transfer reduction, decoding operations avoidance, together with a clever use of the available bandwidth, has a strong impact on the efficiency of maintenance operation: the time to repair a failed node is dramatically reduced thus enhancing the whole reliability of the system.

The rest of the paper is organized as follows. We first review the background on maintenance techniques using erasure codes in Section 2. Our novel approach is presented in Section 3 and analyzed in Section 4. We then evaluate and compare it against state of the art approaches in Section 5. Finally, we present related work in Section 6 and conclude this paper.

2. MOTIVATION AND BACKGROUND

2.1 Maintenance in Storage Systems

Distributed storage systems are designed to provide reliable storage service over unreliable components [6][14][21][27]. One of the main challenges of such systems is their ability to overcome unavoidable component failures [13][31]. Fault tolerance usually relies on data redundancy; the classical triplication is the storage policy adopted by Hadoop [28] or the Google file system [14] for example. Data redundancy must be complemented with a maintenance mechanism able to recover from the loss of data when failures occur in order to preserve the reliability guarantees of the system over time. Maintenance has already lain at the very heart of numerous storage systems design [3][12][16][29]. Similarly, reintegration, which is the capability to reintegrate replicas stored on a node wrongly declared as failed, was shown in [5] to be one of key techniques to reduce the maintenance cost. All these studies focused on the maintenance of replicas. While plain replication is easy to implement and easy to maintain, it suffers from a high storage overhead, typically $x$ instances of the same file are needed to tolerate $x - 1$ simultaneous failures. This high overhead is a growing concern especially as the scale of storage systems keeps increasing. This motivates system designers to consider erasure codes as an alternative to replication. Yet, using erasure codes significantly increases the complexity of the system and challenges designers for efficient maintenance algorithms.

2.2 Erasure Codes in Storage Systems

Erasure codes have been widely acknowledged as much more efficient than replication [32] with respect to storage overhead. More specifically, Maximum Distance Separable (MDS) codes are optimal: for a given storage overhead (i.e., the rate between the original quantity of data to store and the quantity of data including redundancy), MDS codes provide the optimal efficiency in terms of data availability. Let us now remind the reader about the basics of an MDS code $(n,k)$: a file to store is split into $k$ chunks, encoded into $n$ blocks with the property that any subset of $k$ out of $n$ blocks suffices to reconstruct the file. Thus, to reconstruct a file of $M$ Bytes one needs to download exactly $M$ Bytes, which corresponds to the same amount of data as if plain replication were used. Reed-Solomon codes are a classical example of MDS codes, and are already deployed in cloud-based storage systems [4][13]. However, as pointed out in [25], one of the major concern of erasure codes lies in the maintenance process, which incurs an important overhead in terms of bandwidth utilization as well as in decoding operations as explained below.

Maintenance of Erasure Codes.

When a node is declared as failed, all blocks of the files it was hosting need to be re-created on a new node; we call this operation a repair in the sequel. The repair process works as follows (see Figure 1): to repair one block of a given file, the new node first needs to download $k$ blocks of this file (i.e., corresponding to the size of the file) to be able to decode it. Once decoded, the new node can re-encode the file and then regenerate the lost redundant block. This must be iterated for all the lost blocks. Three issues arise:

1. Repairing one block (typically a small part of a file) requires the downloading of enough blocks by the new node (i.e. $k$) to reconstruct the entire file, and this...
must be done for all the blocks previously stored on the failed node.

2. The new node must then decode the file, though it does not want to access it. Decoding operations are known to be time consuming especially for large files.

3. Reintegrating a node which has been wrongfully declared as faulty is almost useless. This is due to the fact that the new blocks created during the repair operation have to be strictly identical to the lost ones for this is necessary to sustain the coding strategy \(^2\). Therefore reintegrating a node results in having two identical copies of the involved blocks (the reintegrated ones and the new ones). Such blocks can only be useful if either the reintegrated node or the new node fails but not in the event of any other node failure.

In order to mitigate these drawbacks, various solutions have been suggested. Lazy repairs for instance as described in \([3]\) consists in deliberately delaying the repairs, waiting for a successive amount of defects before repairing all the failures together. This enables to repair multiple failures while only suffering from bandwidth (i.e. data transferred) and decoding overhead once. However delaying repairs leaves the system more vulnerable in case of a burst of failures. Architectural solutions have also been proposed, as for example the Hybrid strategy \([26]\). This consists in maintaining one full replica stored on a single node in addition to multiple encoded blocks. This extra replica is thus utilized when repairs have to be triggered. However maintaining an extra replica on a single node significantly complicates the design, while incurring scalability issues. Finally, new classes of codes have been designed \([11,19]\) which trade optimality in order to offer a better tradeoff between storage, reliability and maintenance efficiency.

**A Case for Random Codes.**

In this paper, we argue that random linear codes (random codes for short) may offer an appealing alternative to classical erasure codes in terms of storage efficiency and reliability, while considerably simplifying their maintenance process. Random codes have been initially evaluated in the context of distributed storage systems in \([1]\). Authors showed that random codes can provide an efficient fault tolerant mechanism with the property that no synchronization between nodes is required. Instead, the way blocks are generated on each node is achieved independently in such a way that it will fit the coding strategy with high probability. Avoiding such synchronization is crucial in distributed settings, as also demonstrated in \([15]\).

The basic principle of encoding a file using random codes is simple: each file is divided into \(k\) chunks and the blocks stored for reliability are created as random linear combinations of these \(k\) blocks (see Figure 2). All blocks, along with their associated coefficients, are then stored on \(n\) different nodes. Note that the additional storage space required for the coefficients is typically negligible compared to the size of each block.

In order to reconstruct a file initially encoded with a given \(k\), one needs to download \(k\) different blocks of this file.
ory on random matrix over finite field ensures that if one takes $k$ random vectors of the same subspace, these $k$ vectors are linearly independent with a probability which can be made arbitrary close to one, depending on the field size [1]. This is a key difference with erasure codes, avoid any synchronization between nodes. In other words, an encoded file can be reconstructed as soon as any set of $k$ encoded blocks is collected, and as already mentioned, this is optimal (MDS codes).

3. CLUSTERED NETWORK CODING

Our CNC system is designed to sustain a predefined level of reliability, i.e. of data redundancy, by recovering from failures with a limited impact on performances. We assume that the failure detection is performed by a monitoring system, the description of which is out of the scope of this paper. We also assume that this system triggers the repair process, assigning new nodes to replace the faulty ones, in charge of recovering the lost data and store it.

The predefined reliability level is set by the storage system operator. This reliability level then directly translates into the redundancy factor to be applied to files to be stored, with parameters $k$ (number of blocks sufficient to retrieve a file) and $n$ (total number of redundant blocks for a file). A typical scenario for using CNC is a storage cluster like in the Google File System [13], where files are streamed into extents of the same size, for example 1GB as in Windows Azure Storage [4]. These extents are erasure coded in order to save storage space.

3.1 A Cluster-based Approach

To provide an efficient maintenance, CNC relies on (i) hosting all blocks related to a set of files on a single cluster of nodes, and (ii) repairing multiple files simultaneously. This is achieved by combining the use of random codes, network coding and a cluster-based placement strategy. This enables to repair several files simultaneously, without requiring computationally intensive decoding operations, thus factorizing the costs of repair across the several multiple files stored by the faulty node. To this end, the system is partitioned into disjoint clusters of $n$ nodes, so that each node of the storage system belongs to one and only one cluster. Each file to be stored is encoded using random codes and is associated to a single cluster. All blocks of a given file are then stored on the $n$ nodes of the same cluster. In other words, CNC placement strategy consists in storing blocks of two different files belonging to the same cluster on the same set of nodes, as illustrated on Figure 3.

In such a setup, the storage system manager (e.g. the master node in the Google File System [13]) only needs to maintain two data structures: an index which maps each file to one cluster and an index by cluster which contains the set of the identifier of nodes in this cluster. This simple data placement scheme leads to significant data transfer gains and better load balancing, by clustering operations on encoded blocks, as explained in the remaining part of this section.

3.2 Maintenance of CNC

When a node failure is declared, the maintenance operation must ensure that all the blocks hosted on the faulty node are repaired in order to preserve the redundancy factor and hence the predefined reliability level of the system. Repair is usually performed at the granularity of a file. Yet, a node failure typically leads to the loss of several blocks, involving several files. This is precisely this characteristic that CNC leverages. Typically, when a node fails, multiple repairs are triggered, one for each particular block of one file that the failed node was storing. Traditional approaches using erasure codes actually consider a failed node as the failure of all of its blocks. Instead, the novelty of CNC is to leverage network coding at the node level, i.e. between different files on a particular cluster. This is possible since CNC placement strategy clusters files so that all nodes of a cluster store the same files. This technical shift enables to significantly reduce the data to be transferred during the maintenance process.

3.3 An Illustrating Example

To provide the intuition of CNC, and before generalizing in the next section, we now describe a simple example (see Figure 4) involving two files and a 4 node cluster. We consider two files $X$ and $Y$ of size $M = 1024$ MB, encoded with random codes ($k = 2, n = 4$), stored on the 4 nodes of the same cluster (i.e. Nodes 1 to 4). File $X$ is chunked into $k = 2$ chunks $X_1$, $X_2$ as well as file $Y$ into chunks $Y_1$ and $Y_2$. Each node stores two encoded blocks, one related to file $X$ and the other to file $Y$ which are respectively a random linear combination of $\{X_1, X_2\}$ and $\{Y_1, Y_2\}$. Each block has a size of $\frac{M}{k} = 512$ MB, thus each node stores a total of $2 \times 512 = 1024$ MB. We now consider the failure of Node 4.

In a classical repair process, the new node asks to $k = 2$
Figure 4: Example of a CNC repair process, for the repair of a new node in a cluster of 4 (with \( k = 2, n = 4 \)).

The intuition is that, as coefficients of these equations are random, these two systems are always solvable w.h.p.. The new node then makes two different linear combinations of the three received blocks according to the previously computed coefficients, \((A, B, C)\) and \((D, E, G)\) in the example. Thereby it creates two new independent random blocks, one related to file X and one to file Y. The repair is then performed, saving the bandwidth consumed by the transfer of one block i.e., 512 MB in this example.

### 3.4 CNC: The General Case

We now generalize the previous example for any \( k \). We first define a RepairBlock object: a RepairBlock is a random linear combination of two encoded blocks of two different files stored on a given node. RepairBlocks are transient objects which only exist during the maintenance process i.e., RepairBlocks are never stored permanently.

We are now able to formulate the core technical result of this paper; the following proposition applies in a context where different files are encoded using random codes with the same \( k \), and the encoded blocks are placed according to the cluster placement described in the previous section.

**Proposition 1.** In order to repair two different files, downloading \( k + 1 \) RepairBlocks from \( k + 1 \) different nodes is a sufficient condition.

Repairing two files jointly actually comes down to create one new random block for each of the two files; the formal
proof of this proposition is given in Appendix. This proposition implies that instead of having to download $2k$ blocks as with Reed-Solomon codes when repairing, CNC decreases that need to only $k + 1$. Other implications and analysis are detailed in the next section.

We shall notice that the encoded blocks of the two files do not need to have the same size. In case of different sizes, the smallest is simply zero-padded during the network coding operations as usually done in this context; padding is then removed at the end of the repair process.

Figure 5 describes one iteration of the process at the end of which two encoded blocks are repaired. Each of the $k + 1$ nodes sends a RepairBlock to the new node, which then combines them to restore the two lost encoded blocks. However, nodes usually store far more than two blocks, implying multiple iterations of the process described in Figure 5. More formally, to restore a failed node which was storing $x$ blocks, the repair process must be iterated $\frac{x}{2}$ times. In fact, as two new blocks are repaired during each iteration, the number of iteration is halved compared to the classical repair process. Note that in case of an odd number of blocks stored, the repair process is iterated until only one block remains. The last block is repaired downloading $k$ blocks of the corresponding file which are then randomly combined to conclude the repair. The overhead related to the repair of the last block in case of an odd block number vanishes with a growing number of blocks stored.

The fact that the repair process must be iterated several times can also be leveraged to balance the bandwidth load over all the nodes in the cluster. Only $k + 1$ nodes over the $n$ of the cluster are selected at each iteration of the repair process; as all nodes of the cluster have a symmetrical role, a different set of $k + 1$ nodes can be selected at each iteration. In order to leverage the whole available bandwidth of the cluster, CNC makes use of a random selection of these $k + 1$ nodes at each iteration. In other words, for each round of the repair process, the new node selects $k + 1$ nodes over the $n$ cluster nodes randomly. Doing so, we show that every node is evenly loaded i.e., each node sends the same number of RepairBlocks in expectation.

More formally, let $N$ be the number of RepairBlocks sent by a given node. In a cluster where $n$ nodes participate in the maintenance operation, for $T$ iterations of the repair process, the average number of RepairBlocks sent by each node is:

$$E(N) = \frac{k + 1}{n}$$

The proof is given in Appendix. An example illustrating this proposition is provided in the next section.

4. CNC ANALYSIS

The novel maintenance protocol proposed in the previous section enables (i) to significantly reduce the amount of data transferred during the repair process; (ii) to balance the load between the nodes of a cluster; (iii) to avoid computationally intensive decoding operations and finally (iv) to provide useful node reintegration. The benefits are detailed below.

4.1 Transfer Savings

A direct implication of Proposition 1 is that for large enough values of $k$, the data to transfer required to perform a repair is halved; this directly results in a better usage of available bandwidth within the datacenter. To repair two files in a classical repair process, the new node needs to download at least $2k$ blocks to be able to decode each of the two files. Then the ratio $\frac{k + 1}{2k}$ (CNC over Reed-Solomon) tends to $1/2$ as larger values of $k$ are used.

The exact necessary amount of data $\sigma(x, k, s)$ to repair $x$ blocks of size $s$ encoded with the same $k$ is given as follows:

$$\sigma(x, k, s) = \begin{cases} \frac{s}{x}k\frac{k+1}{2} & \text{if } x \text{ is even} \\ \frac{s}{x}\frac{k+1+k-1}{x} & \text{if } x \text{ is odd} \end{cases}$$

An example of the transfer savings is given in Figure 6 for $k = 16$ and a file size of 1GB.
We described in CNC, through Proposition 1, the need to repair lost files by groups of two. One can wonder whether there is a benefit in grouping more than two files during the repair. In fact, a simple extension of Proposition 1 is that to there is a benefit in grouping more than two files during the restore.

4.2 Load Balancing

As previously mentioned, when a node fails, the repair process is iterated as many times as needed to repair all lost blocks. CNC ensures that the load over remaining nodes is balanced during maintenance; Figure 7 illustrates this. This example involves a 5 node cluster, storing 10 different files encoded with random codes \( (k = 2) \). Node 5 has failed, involving the loss of 10 blocks of the 10 files stored on that cluster. Nodes 1 to 4 are available for the repair process.

CNC provides a load balanced approach, inherent to the random selection of the \( k + 1 = 3 \) nodes at each round. In addition, only \( T = 5 \) iterations of the repair process are necessary to recreate the 10 new blocks, as each iteration enables to repair 2 blocks at the same time. The total number of RepairBlocks sent during the whole maintenance is \( T \times (k+1) = 15 \), whereas the classical repair process needs to download 20 encoded blocks. The random selection ensures in addition that the load is evenly balanced between the available nodes of the cluster. Here, nodes 1, 2 and 4 are selected during the first repair round, then nodes 2, 3 and 4 during the second round and so forth. The total number of RepairBlocks is balanced between all available nodes, each sending \( \frac{T \times (k+1)}{n} = \frac{15}{4} = 3.75 \) RepairBlocks on average. As a consequence of using the whole available bandwidth in parallel, contrary to sequentially fetching blocks for only a subset of nodes, the Time To Repair (TTR) a failed node is also greatly reduced. This is confirmed experimentally in Section 5.

4.3 No Decoding Operations

Decoding operations are known to be time consuming and should therefore only be necessary in case of file accesses. While the use of classical erasure codes requires such decoding to take place upon repair, CNC avoids those cost-intensive operations. In fact, no file needs to be decoded at any time in CNC: repairing two blocks only requires to compute two linear combinations instead of decoding the two files. However the output of our repair process is strictly equivalent if files had been decoded. This greatly simplify the repair process over classical approaches. As a consequence, the time to perform a repair is reduced by order of magnitude compared to the classical reparation process, especially when dealing with large files as confirmed by our experiments (Section 5).

4.4 Reintegration

The decision to declare a node as failed is usually performed using timeouts; this is typically a decision prone to errors. In fact, nodes can be wrongfully timed-out and can reconnect once the repair is done. While the longer the timeouts, the fewer errors are made, adopting large timeouts may jeopardize the reliability guarantees, typically in the event of burst of failures. The interest of reintegration is to be able to leverage the fact that nodes which have been wrongfully timed-out are reintegrated in the system. While this idea has already been explored using replication, reintegration has not been addressed when using erasure codes.
As previously mentioned, when using classical erasure codes, the repaired blocks have to be strictly identical to the lost ones. Therefore reintegrating a failed node in the system is almost useless for this results in two identical copies of the lost and repaired blocks. Such blocks can only be useful in the event of the failure of two specific nodes, the wrongfully timed-out node and the new node.

On the contrary, reintegrating is always useful when deploying CNC. More precisely, every single new block can be leveraged to compensate for the loss of any other block and therefore are useful in the event of the failure of any node. Indeed, new created blocks are simply new random blocks, thus different from the lost ones while being functionally equivalent. Therefore each new block contributes to the redundancy factor of the cluster. Assume that a node which has been wrongfully declared as failed returns into the system. A repair has been performed to sustain the redundancy factor while it turned out not to be necessary. This only means that the system is now one repair process ahead and can leverage this unnecessary repair to avoid triggering a new instance of the repair protocol when the next failure occurs.

5. EVALUATION

In order to confirm the theoretical savings provided by the CNC repair protocol, in terms of bandwidth utilization and decoding operations, we deployed CNC over a public experimental platform. We describe hereafter the implementation of the system and CNC experimental results.

5.1 System Overview

We implemented a simple storage cluster with an architecture similar to Hadoop [28] or the Google File System [14]. This architecture is composed of one tracker node that manages the metadata of files, and several storage nodes that store the data. This set of storage nodes forms a cluster as defined in Section 3. The overview of the system architecture is depicted in Figure 8. Client nodes can PUT/GET the data directly to the storage nodes, after having obtained their IP addresses from the tracker. In case of a storage node failure, the tracker initiates the repair process and schedules the repair jobs.

All files to be stored in the system are encoded using random codes with the same k. Let n be the number of storage nodes in the cluster, then n encoded blocks are created for each file, one for each storage node. Remind that the system can thus tolerate n − k storage node failures before files are lost for good.

**PUT/GET and Maintenance Operations.**

In the case of a PUT operation, the client first encodes blocks. The coefficients of the linear combination associated to each encoded block are appended at the beginning of the block. Those n encoded blocks are sent to the n storage nodes of the cluster using a PUT_BLOCK_MSG. A PUT_BLOCK_MSG contains the encoded information, as well as the hash of the corresponding file. Upon receipt of a PUT_BLOCK_MSG, the storage node stores the encoded block using the hash as filename.

To retrieve the file, the client sends a GET_BLOCK_MSG to at least k out of the n nodes of the cluster. A GET_BLOCK_MSG only contains the hash of the file to be retrieved. Upon receipt of a GET_BLOCK_MSG the storage node sends the block corresponding to the given hash. As soon as the client has received k blocks, the file can be recovered.

In case of a storage node failure, a new node is selected by the tracker to replace the failed one. This new node sends an ASK_REPAIRBLOCK_MSG to k + 1 storage nodes. An ASK_REPAIRBLOCK_MSG contains the two hashes of the two blocks which have to be combined following the repair protocol described in Section 3. Upon receipt of an ASK_REPAIRBLOCK_MSG, the storage node combines the two encoded blocks corresponding to the two hashes, and sends the resulting block back to the new node. As soon as k + 1 blocks are received, the new node can regenerate two lost blocks. This process is iterated until all lost blocks are repaired.

5.2 Deployment and Results

We deployed the system previously described on the Grid5000 execution platform. The experiment ran on 33 nodes connected with a 1GB network. Each node has 2 Intel Xeon L5420 CPUs 2.5 GHz, 32GB RAM and a 320GB hard drive. We randomly chose 32 storage nodes to form a cluster, as defined in Section 3. The last remaining node was selected as the tracker. All files were encoded with k = 16, and we assumed that the size of each inserted file is 1GB. This size is used in Windows Azure Storage for sealed extents which are erasure coded [4].

**Scenario.**

In order to evaluate our maintenance protocol, we implemented a first phase of i files insertion in the cluster, and artificially triggered a repair during the second phase. Accord-
ing to the protocol previously described, the tracker selects a new node to replace the faulty node, to which it sends to the list of IP addresses of the storage nodes. The new node then directly asks RepairBlocks to storage nodes, without any intervention of the tracker, until it recovers as many encoded blocks as the failed node was storing. We measured the time to repair a failed node depending on the number of blocks it was hosting. The time to repair is defined as the time between the reception of the list of IPs, and the time all new encoded blocks are effectively stored on the new node. We compared CNC against a classical maintenance mechanism (called RS), which would be used with Reed-Solomon codes as described in Section 2.2 and with standard replication. All the presented results are averaged on three independent experiments. This small number of experiments can be explained by the fact that Grid5000 enables to make a reservation on a whole cluster of nodes in isolation ensuring that experiments are highly reproducible and we observed a standard deviation under 2 seconds for all values.

Coding.

We developed a Java library to deal with arithmetic operations over a finite field\footnote{This library will be made public along with the paper.} in this experiment, arithmetic operations are performed over a finite field with $2^{16}$ elements as it enables to treat data as a stream of unsigned short integers (16 bits). Additions and subtractions correspond to XOR operations between two elements. Multiplications and divisions are performed in the logspace using lookup tables which are computed offline. This library enabled us to implement classical matrix operations over finite fields, such as linear combinations, encoding and decoding of files.

We measure the encoding time when using random codes for various code rates, depending on the size of the file to be encoded. Results are depicted on Figure 9. We show that for a given $(k, n)$ the encoding time is clearly linear with the file size. For example with $(k = 16, n = 32)$ the encoding time for a file of size 512MB and 1GB are respectively 143 and 272 seconds. In addition, the encoding time increases with $k$ and with the code rate, as more encoded blocks have to be created. For instance, a file of 1GB with $k = 16$ is encoded in 272 seconds for a code rate 1/2 ($n = 32$), whereas 390 seconds are necessary for a code rate 1/3 ($n = 48$).

Transfer Time.

We evaluated in this experiment the time to transfer the whole quantity of data needed to perform a complete repair for CNC, RS and replication, depending on the number of blocks to be repaired. In order to quantify the gains provided by CNC in isolation, we disabled the load balancing part of the protocol in this experiment. In other words, the same set of nodes is selected for all iterations of the repair process. The results are depicted on Figure 10.

Firstly, we observe on the figure that CNC consistently outperforms the two alternative mechanisms. As CNC incurs the transfer of a much smaller amount of data, the time to transfer the blocks during the repair process is greatly reduced compared to both RS and replication. For instance, to download the necessary quantity of data to repair a node which was hosting 10 blocks related to 10 different files, CNC only requires 64 seconds whereas RS and replication requires respectively 95 and 154 seconds on average. It should also be noted that no coding operations are done in this experiment, except for CNC as nodes have to compute a random linear combination of their encoded blocks to create a RepairBlock before sending it. This time is taken into account, thus explaining why the transfer time for CNC is not exactly halved compared to RS.

A second observation is that CNC also scales better with the number of files to be repaired. As opposed to CNC, both RS and replication involve transfer times for multiple files which are strictly proportional to the time to transfer a single file. For example RS and CNC requires 9 seconds to download a single file, but RS requires 95 seconds to download 10 files, while CNC only requires 64 seconds for the same operation.

Finally, replication leads to the highest time to transfer.
This is mainly due to the fact that replication does not leverage parallel downloads from several nodes as opposed to CNC and RS. Yet replication does not suffer from computational costs, which can dramatically increase the whole repair time of a failure as shown in the next section.

**Repair Time.**

In this experiment, we measured the whole repair time of a failure, depending on the number of blocks (related to different files) the failed node was storing. The results, depicted on Figure 11, include both the transfer times, evaluated in the previous section, as well as coding times. Thereby it represents the effective time between a failure is detected and the time it has been fully recovered. As replication does not incur any coding operations, the time to repair is simply the time to transfer the files. Note that for the sake of fairness, we enable the load balancing mechanism both for CNC and RS.

Figure 11 shows that the repair time is dramatically reduced when using CNC compared to RS, especially with an increasing number of files to be repaired. For instance to repair a node which was hosting 10 blocks related to 10 different files, CNC and replication require respectively 165 and 154 seconds while RS needs 1620 seconds on average. These time savings are mainly due to the fact that decoding operations are avoided in CNC. In other words, CNC saves time compared to replication during the data transfer, but these savings are cancelled out due to linear combination computations. Finally our experiments show that, as opposed to RS, CNC scales as well as replication with the number of files to be repaired.

**Load Balancing.**

As shown in Section 3.4, CNC provides a natural load balancing feature. The random selection of nodes from which to download blocks during the maintenance process ensures that the load is evenly balanced between nodes. In this section, firstly we experimentally verify that nodes are evenly loaded, then we evaluate the impact of this load balancing on the transfer time for both CNC and RS.

Figure 12 shows the number of blocks sent by each of the 32 nodes of the cluster for a repair of a node which was storing 100 blocks when using CNC. This involves 50 iterations of the protocol, where at each iteration, $k + 1 = 17$ distinct nodes send a RepairBlock. We observe that all nodes send a similar number of blocks, i.e., nearly 26, in expectation. This is consistent with the expected value analytically computed, according to Equation 1 as $25 \times \frac{17}{32} = 2.5625$.

Figure 13 depicts the transfer time for both RS and CNC depending on the number of files to be repaired. We compare the transfer time between the load balanced approach (CNC-LB and RS-LB), and its counterpart which involves a fixed set of nodes, as done in Section 5.2. Results show that transfer times are reduced when load balancing is enabled, as the whole available bandwidth can be leveraged. In addition, time savings due to the load balance increases as more files have to repaired.

6. RELATED WORK

The problem of efficiently maintaining erasure-coded content has triggered a novel research area both in theoreti-
tical and practical communities. Design of novel codes tailored for networked storage systems has emerged, with different purposes.

For instance, in a context where partial recovering may be tolerated, priority random linear codes have been proposed in [22] to offer the property that critical data has a higher opportunity to survive node failures than data of less importance. Another point in the code design space is provided by self-repairing codes [24] which have been especially designed to minimize the number of nodes contacted during a repair thus enabling faster and parallel replenishment of lost redundancy.

In a context where bandwidth is the scarcest resource, network coding has been shown to be a promising technique which can serve the maintenance process. Network coding was initially proposed to improve the throughput utilization of a given network topology [2]. Introduced in distributed storage systems in [7], it has been shown that the use of network coding techniques can dramatically reduce the maintenance bandwidth. Authors of [7] derived a class of codes, namely regenerating codes which achieve the optimal trade-offs between storage efficiency and repair bandwidth. In spite of their attractive properties, regenerating codes are mainly studied in an information theory context and lack of practical insights. Indeed, this seminal paper provides theoretical bounds on the quantity of data to be transferred during a repair, without supplying any explicit code constructions. The computational cost of a random linear implementation of these codes can be found in [10]. A broad overview of the recent advances in this research area are surveyed in [9].

Very recently, authors in [20] and [25] have designed new code especially tailored for cloud systems. Paper [20] proposed a new class of Reed-Solomon codes, namely rotated Reed-Solomon codes with the purpose of minimizing I/O for recovery and degraded read. Simple Regenerating Codes, introduced in [25], trade storage efficiency to reduce the maintenance bandwidth while providing exact repairs, and simple XOR implementation.

Some other recent works [17][18] aim to bring network coding into practical systems. However they rely on code designs which are not MDS, thus consuming more storage space, or are only able to handle a single failure hence limiting their application context.

7. CONCLUSION

While erasure codes, typically Reed-Solomon, have been acknowledged as a sound alternative to plain replication in the context of reliable distributed storage systems, they suffer from high costs, both bandwidth and computationally-wise, upon node repair. This is due to the fact that for each lost block, it is necessary to download enough blocks of the corresponding file and decode the entire file before repairing.

In this paper, we address this issue and provide a novel code-based system providing high reliability and efficient maintenance for practical distributed storage systems. The originality of our approach, CNC, stems from a clever cluster-based placement strategy, assigning a set of files to a specific cluster of nodes combined with the use of random codes and network coding at the granularity of several files. CNC leverages network coding and the co-location of blocks of several files to encode files together during the repair. This provides a significant decrease of the bandwidth required during repair, avoids file decoding and provides useful node reintegration. We provide a theoretical analysis of CNC. We also implemented CNC and deployed it on a public testbed. Our evaluation shows dramatic improvement of CNC with respect to bandwidth consumption and repair time over both plain replication and Reed-Solomon-based approaches.

8. ACKNOWLEDGMENT

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APPENDIX

Proof of Proposition 1

Let \( S_N \) be the random variable defined by the linear combination of \( N \) random variables \( \{X_1, X_2, \ldots, X_N\} \). These \( N \) random variables are independent and take their values uniformly in the finite field \( \mathbb{F}_q \).

Proof. Let \( S_N \) be the random variable defined by the linear combination of \( N \) random variables \( \{X_1, X_2, \ldots, X_N\} \). These \( N \) random variables are independent and take their values uniformly in the finite field \( \mathbb{F}_q \).
\[ S_N = \sum_{i=1}^{N} \alpha_i X_i \]

with \( \forall i, X_i \in \mathbb{F}_q \), and \( \alpha_i \in \mathbb{F}_q^* \).

We show by recurrence that if \( \forall i, Pr(X_i = x_i) = \frac{1}{q} \) then
\[ Pr(S_N = s_N) = \frac{1}{q^N} \]

The case \( N = 1 \) is trivial. Let first show that for \( N = 2 \) the proposition is true.

\[ S_2 = \alpha_1 X_1 + \alpha_2 X_2 \]
\[ Pr(S_2 = s_2) = Pr(\alpha_1 X_1 + \alpha_2 X_2 = s_2) \]
\[ = \sum_{x_1=0}^{q-1} Pr(X_1 = x_1) Pr(X_2 = \frac{s_2 - \alpha_1 x_1}{\alpha_2}) \]
\[ = \sum_{x_1=0}^{q-1} \frac{1}{q} \frac{1}{q} = \frac{q}{q} \]
\[ = \frac{1}{q} \]

The proposition is thus true for \( N = 2 \). We suppose that it is true for all \( N \), and prove that it is true for \( N + 1 \).

\[ S_{N+1} = S_N + \alpha_{N+1} X_{N+1} \]
\[ Pr(S_{N+1} = s_{N+1}) = Pr(S_N + \alpha_{N+1} X_{N+1} = s_{N+1}) \]
\[ = \sum_{x_{N+1}=0}^{q-1} [Pr(X_{N+1} = x_{N+1}) \times Pr(S_N = s_{N+1} - \alpha_{N+1} x_{N+1})] \]
\[ = \sum_{x_{N+1}=0}^{q-1} \frac{1}{q} \frac{1}{q} = \frac{q}{q} \]
\[ = \frac{1}{q} \]

\[ \square \]

**Definition 1.** A random vector \( \vec{V} \) in a vector space \( X = \text{span}\{X_1, X_2, \ldots, X_k\} \) where \( X_i \in \mathbb{F}_q^i \) is defined as:

\[ V = \sum_{i=1}^{k} \alpha_i X_i \]

where the \( \alpha_i \) coefficients are chosen uniformly at random in the field \( \mathbb{F}_q \), i.e. \( Pr(\alpha_i = \alpha) = \frac{1}{q}, \forall \alpha \in \mathbb{F}_q \).

Let \( X \) be the vector space defined as \( \text{span}\{X_1, X_2, \ldots, X_k\} \). Let \( Y \) be the vector space defined as \( \text{span}\{Y_1, Y_2, \ldots, Y_k\} \). No assumptions are made on \( X_i \) and \( Y_i \) except that they are all in \( \mathbb{F}_q^i \). In fact as \( X_i \) and \( Y_i \) are file blocks, it is not possible to ensure linear independence for example.

Let \( B_x^i \) be an encoded block of the file \( F_x \) stored on node \( i \). \( B_x^i \) is a random linear combination of the \( \{X_1, X_2, \ldots, X_k\} \), thus \( B_x^i \in \text{span}\{X_1, X_2, \ldots, X_k\} = X \) which is a subspace of \( \mathbb{F}_q^i \) of dimension \( \text{Dim}(X) \leq k \).

**Lemma 2.** \( \forall \text{Dim}(X), B_x^i \) is a random vector in \( X \).

**Proof.** Let \( B \) be the largest family of linearly independent vectors of \( \{X_1, X_2, \ldots, X_k\} \)
\[ \forall l | X_l \notin B, \exists \{b_1^l, \ldots, b_j^l\} \text{ such that } X_l = \sum_{j}\{X_j \in B \} b_j^l X_j \]
\[ |B| \leq k \]
\[ \text{Dim}(X) \leq k \]

From Lemma 1 all the coefficients of the linear combination are random over \( \mathbb{F}_q \) thus \( B_x^i \) is a random vector in \( \text{span}(B) \).

As \( \text{span}(B) = \text{span}\{X_1, X_2, \ldots, X_k\} = X \)
Then \( B_x^i \) is a random vector in \( X \). \( \square \)

Let \( D^i \) be the random linear combination of two stored blocks by the node \( i \) with \( i \in [1, k+1] \).

\[ D^i = \delta^i_x B_x^i + \delta^i_y B_y^i \]
\[ = \delta^i_x (\sum_{j=1}^{k} a_j^i X_j) + \delta^i_y (\sum_{l=1}^{k} a_l^i Y_l) \]
\[ = D_x^i + D_y^i \]

By definition, \( D^i \in \text{span}\{X_1, X_2, \ldots, X_k, Y_1, \ldots, Y_k\} \)
\[ D_x^i = \sum_{j=1}^{k} \delta^i_x a_j^i X_j \]
As \( \delta^i_x \) are chosen randomly in \( \mathbb{F}_q \), then from Lemma 1
\[ D_x^i \] is a random vector in \( X \).

Let’s take a family \( \{D_1^i, \ldots, D_k^{i+1}\} \).
As \( \text{Dim}(X) \leq k \) it exists \( \{\alpha_1, \ldots, \alpha_k+1\} \neq 0 \) such that
\[ \sum_{i=1}^{k+1} \alpha_i D_x^i = 0 \]
Then:
\[ \sum_{i=1}^{k+1} \alpha_i D^i = \sum_{i=1}^{k+1} \alpha_i D_x^i + \sum_{i=1}^{k+1} \alpha_i D_y^i \]
\[ = \sum_{i=1}^{k+1} \alpha_i D_y^i \]

As \( \alpha_i \) are chosen independently with \( D_y^i \) then new vector is a random vector in \( Y \). The reasoning is identical to get the new vector in \( X \), thus completing the proof.
Proof of Equation (1)

During the repair process, the load on each node can be evaluated using a Balls-in-Bins model. Balls correspond to a block to be downloaded while bins represent the nodes which are storing the blocks. For each iteration of the repair protocol, k different nodes are selected to send a repair block. This corresponds to throwing k identical balls into n bins, with the constraints that once a bin has received a ball, it can not receive another ball at this round. In other words exactly k different bins are chosen at each round.

\[ \text{Lemma 3. At each round } i, \text{ the probability that a given bin has received one ball is } \frac{k}{n} \]

Proof. Let A be the event "the bin contains one ball at round i". Thus \( \overline{A} \) corresponds to the event "the bin is empty at round i". \( \Pr(A) \) is computed as the number of ways to place the k balls inside the n − 1 remaining bins, over all the possibilities to place the k balls into the n bins.

\[
\begin{align*}
\Pr(A) &= 1 - \Pr(\overline{A}) \\
&= 1 - \frac{\binom{n-1}{k}}{\binom{n}{k}} \\
&= 1 - \frac{k!(n-1-k)!}{n!(n-k)!} \\
&= 1 - \frac{(n-k)!}{n(n-1-k)!} \\
&= 1 - \frac{(n-k)}{n} \\
&= \frac{k}{n}
\end{align*}
\]

\[ \Box \]

Let X be the number of balls into a given bin after t rounds. As the selection at each round are independent, the number of balls into a given bin follows a binomial law : \( X \sim B(t, p) \) with \( p = \frac{k}{n} \). (See Lemma 3) The expected value, denoted E(X), of the Binomial random variable X with parameters t and p is : \( E(X) = tp = t \frac{k}{n} \).