Minimum Duration to Realocate Data in a Cluster

August 27, 2019

1 Introduction

The term "Big Data" refers to the data which is too large to be processed by traditional tools and procedures. This notion emerged in the 1990s and gained momentum in the 2000s, when the term Big Data become popular . Big Data requires to develop new technologies in order to be processed.
In 2019, 4.5 Million of videos are viewed on YouTube, 3.8 Million of Search Queries are done on Google and 188 Million of emails are sent in a minute. Big Data is more than ever a challenge. These Data need to be stored, classified, sorted and analyzed.
With this goal, in 2004, Google has proposed the MapReduce model. MapReduce [4] is a programming model for processing large data set using distributed file system for data storage. It's based on two main operations, the *map* and *reduce* operations, which can be freely written by programmers. The map operation consists on a classification and sorting step. The reduce operation is the processing step. The MapReduce reduce model proposes to rewrite all algorithms for distributed systems in a generic way, in terms of these two operations. Programmers should only focus on writing this two operations. That enables users to manage optimization, parallelization, fault tolerance separately from programming.
To implement this programming paradigm and achieve good performance, many systems have been developed. Most of them use distributed file system where data is co-located with computation. That reduce latency and make easier to go to scale.
The main one is Hadoop [7]. Hadoop manages optimization, parallelization and fault tolerance). It also provides a distributed file system (Hadoop Distributed File System HDFS). Hadoop divides application tasks into many small fragments of work job. In that goal, it has a master/slave architecture. The master splits files (the Input of a MapReduce algorithm) into blocks (typically 128 MB) and distributes them across the HDFS cluster. The master holds metadata information about stored data and direct requests. The slaves serve read and write and propagate replication tasks. Blocks are replicated for fault tolerance.
A main challenge in distributed file systems is *elasticity*. Indeed the ability to automatically shrink and grow clusters of computers on demand as workload change can be a means to achieve good performance. It enables to manage power consumption by adapting the size of the cluster to the client demand. It also enable a better management of the cluster by quickly reallocating resources to other tasks.
By now, elasticity remains a challenge to achieve for cloud. Indeed while cloud utilization fluctuates, the size of infrastructures is fixed. Elasticity in a storage cluster can be achieved by implementing decommission and commission of physical ressources.

- Commission a node in a cluster consists in adding a node to the cluster and bringing it into working condition (in a data cluster, transmitting it data).
- Decommission consists in removing cluster's nodes and reallocated the node's attributes.

Decommission and commission haven't already properly be designed in data cluster. They are still considered as too long to be useful. In fact all data on nodes to decommission has to be recreated (most of time its gigabits or terabits to transfer).

1.1 Related Work

Our goal is to bring elasticity to storage clusters. This question has been previously explored. We present some of related works.

- Sierra [8] is a distributed file storage developed in order to achieve power proportionality (the number of nodes used in the cluster is proportional to the cluster utilization). It powers down servers during throughput without migrating data. So it doesn't use decommission. The limits of Sierra is that it has to keep at least one replica of each file to be able to maintain write availability. This requirement limits elasticity, the cluster can not shrink under $1/r$ of its maximum size where r is the replication factor. Sierra lake of agility. The authors don't try to minimize the time to powering off nodes. Also data layout when turning servers back induces significant migration overhead, impairing system agility.

- Rabbit [1] is a distributed file system that arranges its data layout to achieve power proportionality. As Sierra, it powers down servers (it doesn't use replication). It dispatches primaries in such a way that it can shrink to a small size (≈ 10 percent of total cluster's size). But to achieve this, because of the data layout, Rabbit lost writing bandwidth even when the cluster is at its maximum powering, because primaries replicas are located on 10 percent of nodes. Besides this system induces significant cleanup overhead when shrinking the cluster thus it lakes of agility.

- SpringFS [6] is a distributed file system which uses Sierra [8] and Rabbit [1] ideas but which works on agility. The authors want *to minimize the time to resize their system*. To that goal, depending on workload, their system behaves like Rabbit [1] or Sierra [8]. They provide a continuum between this two systems which minimize their agility impairing.

- KoalaF [5] focuses on sharing resources among applications according to the variation of their workloads over time. It designs a resource manager. The authors goal is to minimize overheads due to communication between the cluster manager and frameworks.

These articles also point out the importance of being able to resize clusters quickly. But a theoretical model given a lower bound of duration of cluster resizing would be relevant in order to assess and improve distributed file systems.

1.2 How Fast Can One Scale Down a Distributed File System

How Fast Can One Scale Down a Distributed File System? [2] is an article which develops a model for decommission time. Our work is based on this paper. The model developed establish a lower bound of decommission's duration and the article also describes experiments wich evaluate the accuracy of the model. A limit of this paper is the strong hypotheses taken to develop the decommission model. It assumes that all cluster nodes have the same amount of data. Besides it assumes that any two nodes share exactly the same amount of data.
To establish the model, the authors consider two cases. First they assume the performance of decommission is limited by storage, then they explore the case where it is limited by the I/O speed. Results (in term of

relative error) are better with the first assumption. In order to evaluate his model the author also develops a modular benchmark Pufferbench [3]. This benchmark evaluate how fast can scale up and down distributed storage systems. It has been designed in order to be easily customized. We modified Pufferbench code and used it to assess our model.

2 Contribution : modelling the decommission time for non-uniform data distributions and validation of the model

This study provides a mathematical model which gives a lower bound for the decommission's duration in a distributed file system. The model aims at a largest scope as possible. It offers generecity by considering that data distribution does not have a particular shape in the cluster. This approach improves the previous model for decommission which considered a fixed and uniform distributed distribution of data. This paper makes the following contributions:

- We present the main assumptions on which our model is based.
- We develop the mathematical model that we used to design the lower bound of duration of decommission. This section is composed of two major parts corresponding to two possible bottlenecks. The first part deals with a network bottleneck while the second part deals with a storage bottleneck.
- We evaluate the accuracy of our model by experiments in a real cluster system and analyze the results

2.1 Model

In this study we consider a cluster of nodes (a node can be a computer). Each node stores information which can't be lost. Nodes can also communicate (for example with a network).

2.1.1 Definition of the decommission

Decommission is a main operation in a cluster. It stands for removing nodes from the cluster. The key point is that data must not be lost after the removal of nodes. Thus the operation consists in recreating nodes content. To recreate data, leaving nodes will send it to other (remaining) nodes. That will rewrite it. In this study each piece of data is replicated (that's often the case in practice) several times in the cluster, there will be several nodes (not only the one which will be removed) that will be able to send information needed to be recreated. Because all data should be recreated during the operation, the number of data replicas should be constant.

2.2 Assumption on the cluster

In this section, we introduce the main hypotheses to establish our model

1) Homogeneous cluster
All nodes have the same characteristics, in particular the same network throughput S_{Net} and the same throughput for reading, writing to storage devices (S_{Read}, S_{Write}).

2) Ideal network
The network is full duplex, data can be sent and received with a throughput of S_{Net} at any time, and there

is no interferences between signals generated by data transmission.

3) Ideal storage

The device must share its I/O time between reads and writes and thus can not sustain simultaneous reads and writes at maximum speed (during any span of time t, if a time $t_{Read} \leq t$ is spent reading, the storage cannot write for more than $t - t_{Read}$, and conversely).

2.2.1 Distribution

- We consider a cluster of N nodes
- We wish to decommission x nodes of a cluster
- The x nodes to decommission have an amount of data D to recreate on the cluster
- The data stores in these x nodes are replicated r times in the cluster
- We know the file distribution of the data that we want to recreate among the cluster F_{rep}. F_{rep} gives for a node n in the cluster, the amount of data that it shares with the nodes in decommission (that is to say the data to recreate) .

So the x nodes to decommission have an amount D of data to recreate and there is also a group of nodes in the cluster which has $(r-1)D$ copies of the D data to recreate.

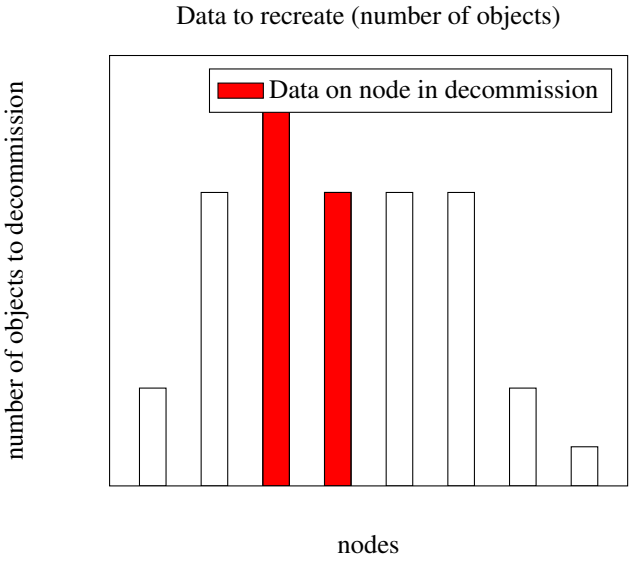

Figure 1: An example of data distribution F_{rep} for eight nodes
Data in red is exactly the data to recreate in the cluster
Data in white is the copy of data to recreate

2.3 A model for the decommission time when the network in the bottleneck

In this part we assume that the network is the bottleneck.
4) Bottleneck network
The network is the component that limits the speed of the operation. The storage throughput is greater than the network throughput.

We want to calculate t_{dec}, a lower bound to decommission time.
We have assumed with hypothesis 2 that the network was full duplex, data can be sent and received at the same time and there is no interference, thus

$$t_{dec} = max(t_{send}, t_{rec}) \tag{1}$$

Where t_{send} is the minimal time to send the data of the decommissioning nodes.
And t_{rec} is the minimal time to receive the data of the decommissioning nodes.

Calculating t_{rec}

We want to calculate t_{dec} a lower bound to decommission time.
We know that the time for decommission is the maximum of the time taken by each node of the cluster during the decommission.

$$t_{dec} = \max_{node} t_n \tag{2}$$

This equation shows that we should distributed uniformly the work between nodes in order to have for all nodes n, n′

$$t_n = t_{n'}$$

where t_n is the time spent by node n to work during decommission

Because we want a lower bound, we focus on the strategy that minimizes the duration to send data. The fastest way to distribute data is to send it uniformly across the cluster. All nodes will receive the same amount of data excepting the nodes in decommission. Since nodes in decommission should leave the cluster, at the end of the decommission they should not have any data and so they shouldn't receive data. Then there are $N-x$ nodes which will receive data We assumed that there is a amount D of data to decommission and that the speed of the network is S_{net} . It follows that

$$t_{rec} = \frac{D}{S_{net}(N-x)} \tag{3}$$

- *D is the data to recreate*
- *N is the number of nodes in the cluster*
- *x is the number of nodes in decommission*

Calculating t_{send}
The time taken to send all the data is the maximum time taken by nodes which send data.
The total data to send is D.
According to this requirements, we should find k and y_s the mean amount of data sent by the most loaded

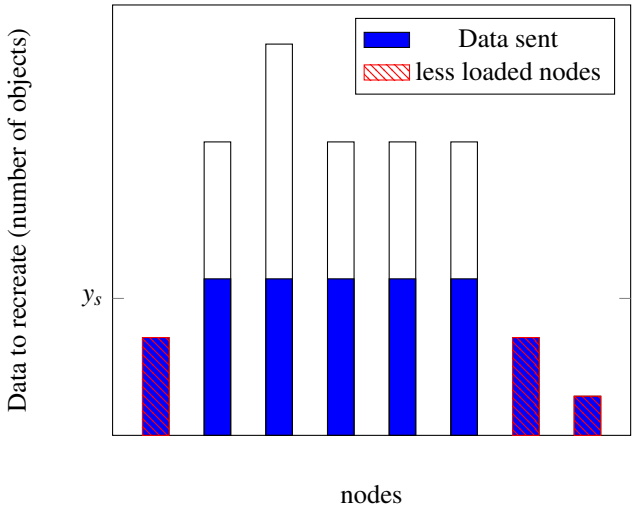

Figure 2: An example of data that should be sent by cluster's nodes

nodes such as

$$\Sigma_{i=1}^{k} F_{rep}(n_i) + \Sigma_{x=k}^{N} y_s = D$$

- $n_1, n_2, ..., n_k$ *are the k less loaded nodes.*
- y_s *is the data sent by the most loaded nodes.*

The idea bellow this formula is to distribute data the most uniformly possible.
Nevertheless the k less loaded nodes will send less data than others because they haven't enough data.
All remaining nodes will send the same amount of data.
Then we have

$$t_{send} = \frac{y_s}{S_{net}} \tag{4}$$

2.4 A model for decommission time when the storage is the bottleneck

In this part we assume that the storage is the bottleneck thus not the network anymore.
5) Bottleneck network
The network is the component that limit the speed of the operation. Storage throughput is greater than S_{net}
Like in section 2.3 we have

$$t_{dec} = \max_{node} t_n$$

Here $t_n = t_{n_{read}} + t_{n_{write}}$ is the time spend by node n to read and write data during decommission. t_n is a sum because of assumption 3 (ideal storage).
Moreover, we know that we should write a quantity

$$D_{write} = D$$

equal to the data hosted in the nodes in decommission.
Nevertheless we don't have $D_{read} = D$ because a node when it has read data to recreate can send this data to multiple nodes. So it should only read an amount

$$D_{read} = \frac{1}{1+\varepsilon} D$$

equal to the *unique* data of the nodes in decommission.
The additional factor $\frac{1}{1+\varepsilon}$ represents the ratio

$$\frac{\text{unique data}}{\text{total data}}$$

among data to replicate.
The ratio variates between 1 and $\frac{1}{r}$ and its mean value is given by

$$\sum_{i=1}^{r} iP(X = i)$$

where $P(X = i)$ is the probability to have exactly i replicas of the same data on the nodes to decommission.

2.4.1 Balancing read and write

Because nodes host different data we differentiate nodes in decommission from each other

- The decommissioning nodes should only read data
- The least loaded nodes will not be able to read as much data than others

Ideally each node should work equally (eq: 2). And t_n should be the same for all nodes n. Thus the decommission time should just be the mean time that nodes have to work to write D_{write} and read D_{read}. Thus

$$t_{dec} = \frac{1}{N}\left(\frac{D_{read}}{S_{read}} + \frac{D_{read}}{S_{write}}\right) \tag{5}$$

Where N is the number of nodes in the cluster.
There will be many situations where this formula is valid, an example of such situation is shown by the figure 3 nevertheless depending on the data distribution, it's not always possible to balance work equally between nodes.

2.4.2 Two cases where work can't be distribute uniformly

The writing operation is the bottleneck
The writing operation is the bottleneck. The less loaded nodes in the cluster can not be able to write enough data to balance the fact that they will read less data. An example of such situation is shown by the figure 4
The reading operation is the bottleneck
The reading operation is the bottleneck. The nodes in decommission will no write data because they should leave the cluster. Thus they can't send enough data to work as others nodes. Then

$$t_{dec} = \frac{D_{read}}{S_{read} x}$$

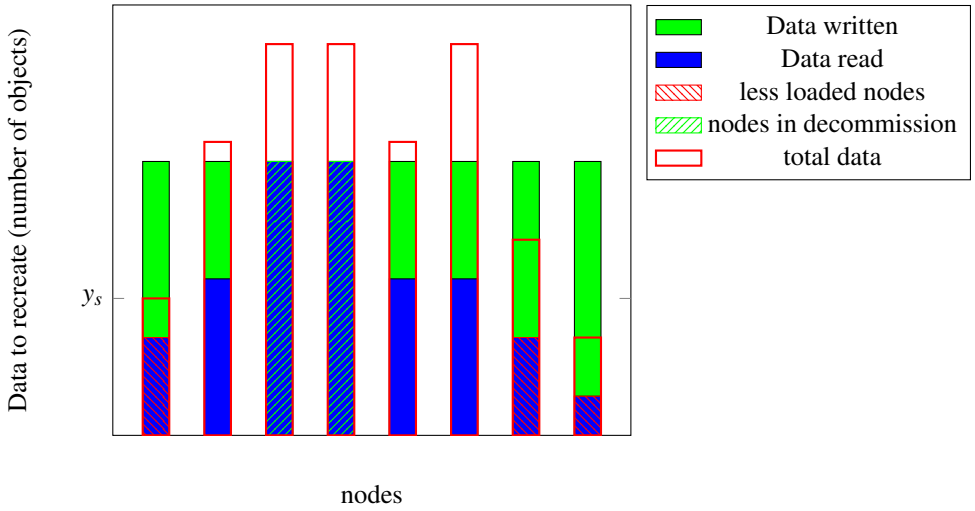

Figure 3: An example of work distribution in the cluster when each node can work equally

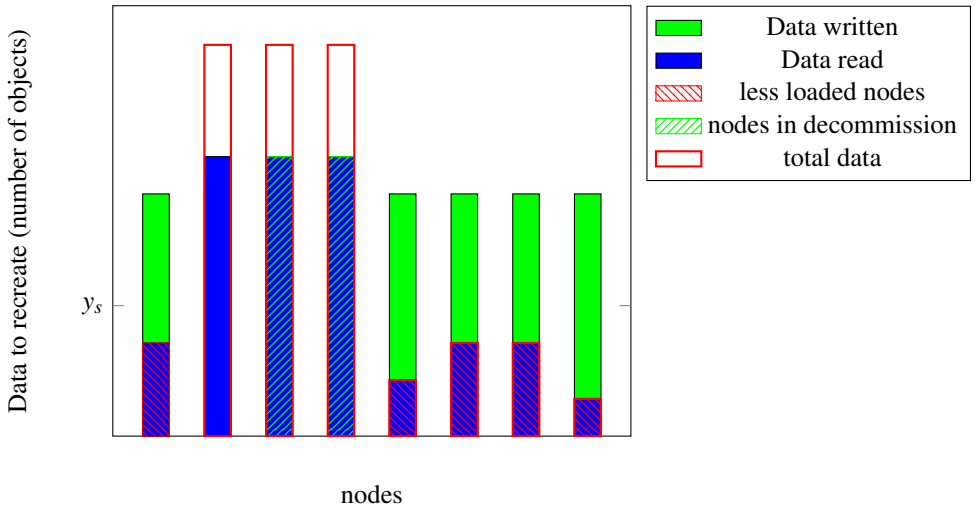

Figure 4: An example of work distribution in the cluster when the writting operation is the bottleneck

An example of such situation is shown by the figure 5
In the most general case, a lower bound for decommission time is

$$t_{dec} = \max_{n}\left(\frac{x_{n_{read}}}{S_{read}} + \frac{x_{n_{write}}}{S_{write}}\right)$$

where $x_{n_{read}}$ and $x_{n_{write}}$ are the data read and write by node n.

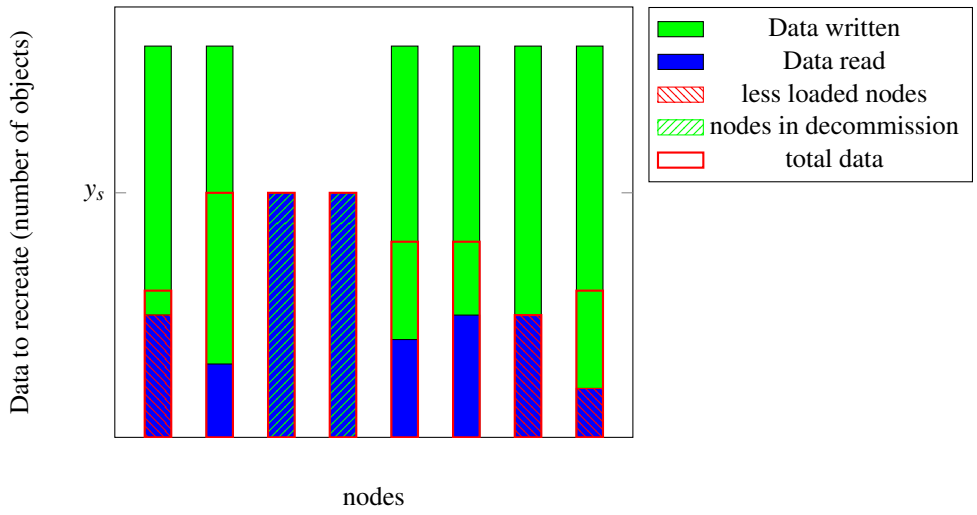

Figure 5: An example of work distribution in the cluster when the reading operation is the bottleneck

3 Validity of the Solution

In this section we assess our formulas. The purpose is to prove the validity of our assumptions and model. Although we provided a lower bound, this lower bound is achievable in real world and thus useful.

3.1 A case-study to assess the results

In order to assess our model, we create a simple case of distribution. We worked with 20 nodes.

- We distributed 40 GiB of data in the nodes to decommission
- We left 6 nodes empty.
- We distributed the remaining data to decommission equally
- We completed by data which not need to be decommissioned so that each node had 40 GiB of data

3.2 Pufferbench

In order to assess our formulas we used Pufferbench [3]. Pufferbench is a benchmark designed to evaluate decommission and commission duration. Pufferbench has been originally developed to validate assumptions of [2] but it has been designed to be easily adapted to other hypotheses. Thus we needed to rewrite a part of Pufferbench code. Then we deployed Pufferbench on a cluster used in the scientific communitie to develop distributed tools.
In this section we will first describe our algorithmic contribution and our extension of Pufferbench.
Then we will present our results and compare them to the theoretical model.

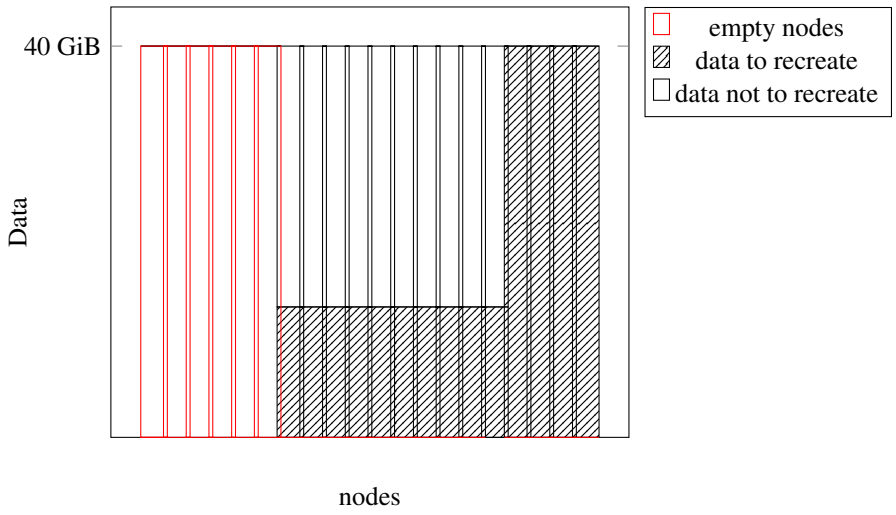

Figure 6: Data Distribution F_{rep} for experiments

3.2.1 Developing Pufferbench

Pufferbench [3] is separated in several components. We focused especially on two components :

- The DataDistributionGenerator
  This component is in charge to distribute data in the cluster.
  It was previously designed to distribute the data uniformly or randomly.
  We developed it to enable it to distribute data has described in 3.1.

- The DataTransfertScheduler
  This component is the "brain" of the decommission, it distributes read/write/send/receive operations.
  It was previously designed to behave like [7] data transfert scheduler.
  We developed it in order that it schedules operations to minimize decommission time.

3.2.2 Experiments Material

For our experiments in Grid5000 [7] we use the Paravance cluster of Rennes. We reserved all this cluster to evict network interferences. The computers of Paravance have 128GB of RAM, two disks(HDD) of 558 GB and the network throuput is 10GB/s. We sent between nodes blocks of size 128MiB. To test the case where the network is the bottleneck we used the cache. Thanks to the cache IO speed is much more greater than network speed, that assures that network will be the bottleneck and not the disk. The network speed was 10 Gb/s. To test the case where the storage is the bottleneck we disable the cache.We used a benchmark to measure the disk speed. We found that it is 210 MB/s for reading operations and 190 MB/s for writing operations.

3.2.3 Results of experiments

We obtain a maximal error between the results and the model of 10 percent when network is the bottleneck (This error has been obtained when there is only one node to decommission and the operation is fast, it

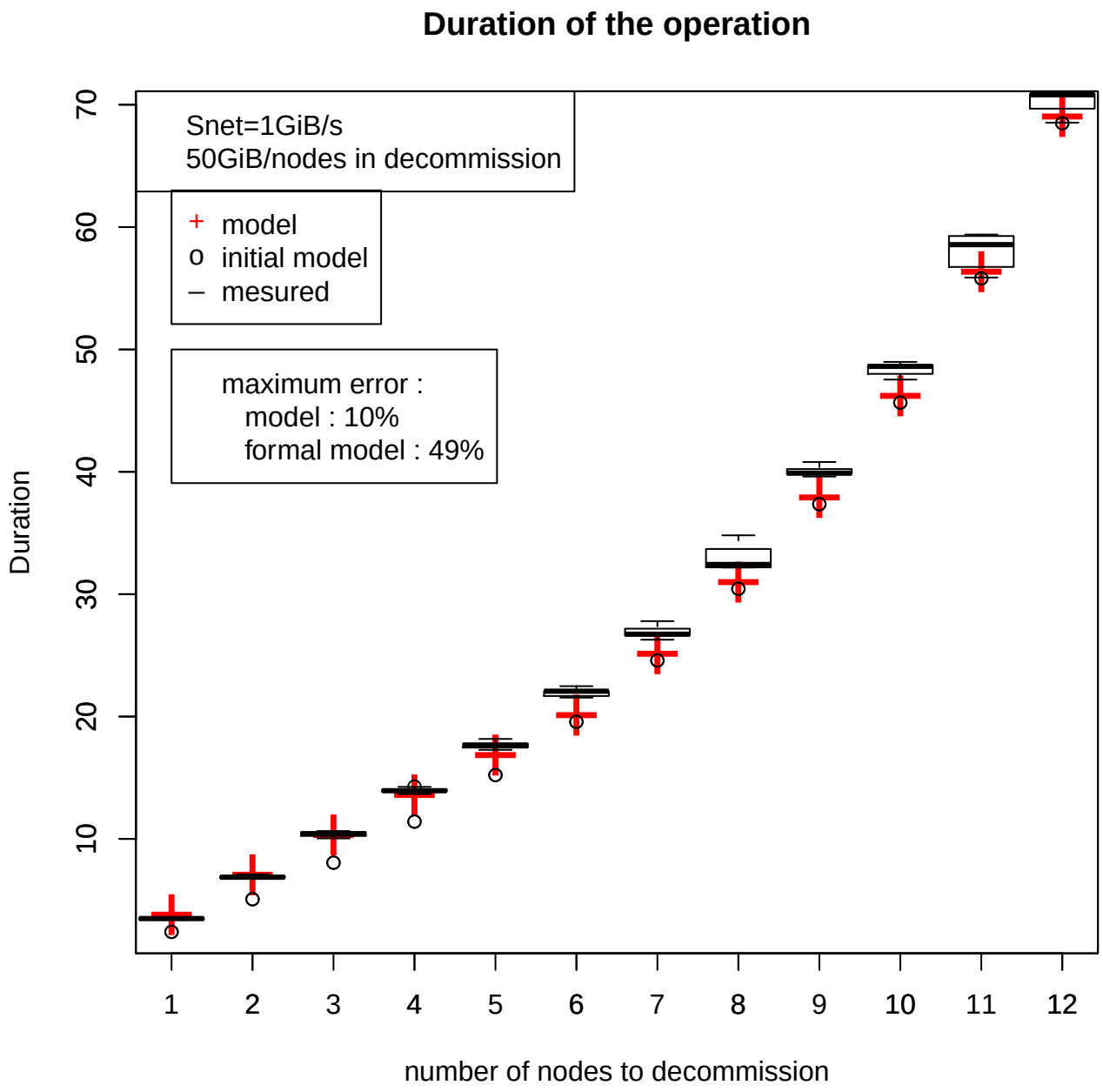

Figure 7: Decommission duration when the network is the bottleneck

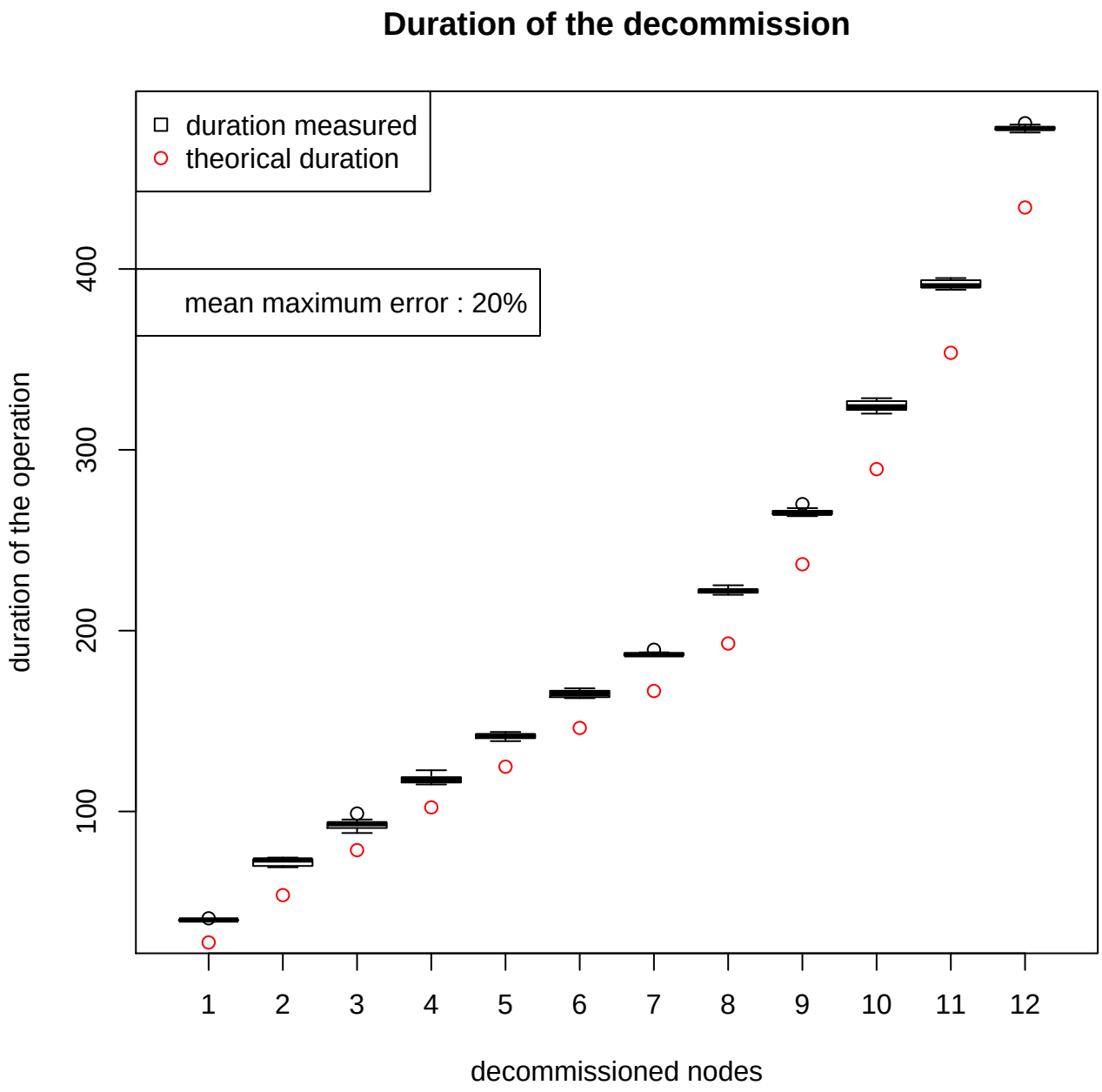

Figure 8: Decommission duration when the storage is the bottleneck

takes only three seconds). The initial model also achieved good performance. Indeed in most of clusters the network speed limits operations thus clusters are optimized to achieve good performance.
When the storage is the bottleneck results are less satisfying (fig 8). On graph we just give the mean maximum error. We repeated each experiment nine times, and we have calculated the maximum error for this nine experiments. We have a mean maximum error of 20 percent on the number of nodes that it's decommissioned. The I/O throughput is very fluctuating, and in our model we considered it stable. That explains the difference between our experimental results and our model.
The error is much less important when the number of nodes in decommissionned increases. That is explained by the fact that latency becomes negligeable only when operation duration is long enough and the standard deviation is weaker. The error should further decrease when decommissionning more nodes in bigger cluster. In pratice many clusters have much more than 20 nodes. For example Yahoo cluster using HDFS, has 5000 nodes.

4 Conclusion

4.1 Future Work

There is still a lot of remaining work related to decommission to prove its interest.

4.1.1 Implementing decommission in a real world

- It needs a study of the energetic consumption of the operation. Explaining the cost and the gain of the operation.
- It needs an application that studies theoretically the impact of the decommission on the application's performance. In this study we have seen that the cost of the decommission is proportional to the amount of data to move. The decommission must be more interesting for applications that use few data compared to computational power. It is also more relevant when there is huge and slow variations.
- It needs to be properly implemented and to be optimized in real world distributed file systems.

4.1.2 Developing strategies to optimize decommission

Because the interest of decommission is highly related to the size of the data to displace, to be relevant each application that would use decommission should focuse on data layout. Some nodes in a cluster will produce less data than others. That would be faster to decommission least loaded nodes. In the second case of this study (subsection 2.4), we have also seen that when data should be read, it's better to decommission nodes which share the same replicas. Also because all data in nodes has to be read on disk, the reading time can be reduced at its minimum (there is no need to find data).

4.1.3 Improve the decommission model

With our experiments we have seen that our model fit better the real world when the network is the bottleneck. Thus it's possible to improve model when the storage is the bottleneck. Particularly that can relevant to study IO throughput variation and consider a model assume a variable speed.
Also there should be situations where there is no network or storage bottleneck but a mixed of it. This situation is also relevant.

4.2 Conclusion

The decommission is a basic operation in cluster management. Thus this operation needs to be study in details. It could bring real solution for storage elasticity. This work focused on studying it in a theoretical and generic manner. We have provided a theoretical lower bound for the duration of the decommission which is independent to data distribution. We first developed a theoretical model then we assessed our results experimentally. The study also enables a better understanding of the decommission and how to optimize this operation.
Nevertheless decommission study isn't a closed matter. And needs practical case of implementation before to be adopted.

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