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Energy-efficient Failure Recovery in Hadoop Cluster

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ENERGY-EFFICIENT FAILURE RECOVERY IN HADOOP CLUSTER

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Based on U.S. Environmental Protection Agency's estimation, only in U.S., billions of dollars are spent on the electricity cost of data centers each year, and the cost is continually increasing very quickly. Energy efficiency is now used as an important metric for evaluating a computing system. However, saving energy is a big challenge due to many constraints. For example, in one of the most popular distributed processing frameworks, Hadoop, three replicas of each data block are randomly distributed in order to improve performance and fault tolerance, but such a mechanism limits the largest number of machine that can be turned off to save energy without affecting the data availability. To overcome this limitation, previous research introduces a new mechanism called covering subset which maintains a set of active nodes to ensure the immediate availability of data, even when all nodes not in the covering subset are turned off. This covering subset based mechanism works smoothly if no failure happens. However, a node in the covering subset may fail.

In this thesis, we study the energy-efficient failure recovery in Hadoop clusters where nodes are grouped into covering and non-covering subsets. Rather than only using the replication as adopted by a Hadoop system by default, we study both replication and erasure coding as possible redundancy mechanisms. We first present a replication based greedy failure recovery algorithm and then introduce an erasure coding based greedy failure recovery algorithm. Moreover, we also develop a recovery aware data placement strategy to further improve the energy efficiency in failure recovery.

To evaluate the algorithms, we simulate node failure recovery in the clusters of different sizes, construct the energy model and analyze the energy consumed during the failure recovery process. The simulation results show that the erasure coding based failure recovery algorithm often outperforms the replication based approach. On average, the former requires 60% of the energy as that of the later and the energy saving increases with the cluster size. In addition, with our recovery aware data placement strategy, the energy consumption for both approaches could be further reduced.

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Chapter 1

Introduction

Enormous data centers are built to support various types of data processing services like email services and searching engine services. Data centers are becoming critical in modern life. According to data center research organization Uptime Institute's survey in May 2011, 36 percent of the large companies surveyed were expecting to exhaust IT capacity within 18 months. That means, they must enlarge their existing data centers or build more data centers. To maintain a data center, a large amount of energy need to be consumed for both computing and cooling [4]. It is reported that in 2010 2% of electricity is used by data centers in US and 1.3% around the world [19]. As data centers continue to grow in size and number, some researchers estimated that by 2012 the cost of electricity for data centers could exceed the cost of the original capital investment [25]. As a result, how to achieve energy efficiency is a major issue for data centers [2].

One typical and effective way for saving computing energy is to shut down idle machines. According to [6] and [20], there is a large portion of idle machines in data centers consuming up to 60% of the total energy. In order to inactivate as many machines as possible to save energy, researchers attempt to dynamically match the number of activate nodes with the current workload [6]. However, it is nontrivial to apply this approach to MapReduce framework which is a popular and powerful programming model for data-intensive cluster computing. First, MapReduce framework stores the data across many nodes in order to provide an affordable storage for multi-petabyte datasets with a good performance and reliability. [16] indicates that data availability requirement prohibits a MapReduce system from shutting down idle nodes even if significant periods of inactivity are observed. During these periods, energy consumed by those idle machines is wasteful. Moreover, since MapReduce provides mechanisms to ensure fault tolerance and load balance which also exert a negative effect on the energy efficiency. By default, a well-known open source MapReduce framework implementation, Hadoop, employs three replications for each data block and the copies are distributed randomly in the cluster. This mechanism actually limits the number of nodes that can be turned off without affecting the data availability.

In order to address this limitation, Leverich et al. introduce a new mechanism which groups machines of a MapReduce cluster into two subsets, i.e., covering and non-covering subsets [16]. At least one replica of all data blocks must be stored in the covering subset nodes. This way, it ensures the immediate availability of the data, even when all nodes in non-covering subset are turned off. With this mechanism, non-covering subset nodes can be turned on or off according to the workload volume without influencing the data availability. It is proved that the covering subset approach can help saving between 9% and 50% of energy consumption. This approach overcomes the aforementioned limitation elegantly and is likely be implemented in many large MapReduce clusters. However, the previous research [16] does not consider the failure recovery problem while it is common to experience some node/disk failure. By default, when one or more nodes become unavailable in the covering subset, all nodes in the non-covering subset will be turned on. This is obviously a very inefficient approach which could largely cancel the energy saving benefits. In this thesis, we investigate the energy efficient failure recovery problem in Hadoop cluster.

Specifically, we study how to restore data with the lowest electricity cost when a node fails in the covering subset.

In Hadoop, as well as most other well-known MapReduce implementations, replication is the default redundancy mechanism used to achieve fault tolerance. Although straightforward, replication leads to high storage overhead. There is another common redundancy technology, erasure coding (i.e., parity schema), which uses an order of magnitude less storage than replication under the same fault tolerance level. However, it demands some extra effort on encoding and decoding the data. Basically, erasure coding divides an object into d fragments, which will be recoded into $d + e$ fragments, where $\frac{d}{d+e} < 1$ represents the rate of encoding. Erasure coding provides flexibility in failure recovery because any d out of the $d + e$ fragments can be used for reconstructing the original d fragments.

In this thesis, we research on the problem of energy efficient failure recovery in Hadoop cluster where only one data replica is kept online. Similar to the covering subset mechanism in paper [16], we divide the Hadoop cluster into three sets, *Fundamental Set (FS)*, *Extended Set(ES)*, and *Waiting Set(WS)*. FS contains a group of active machines that store one replica of all data blocks; WS holds several offline machines which could be used as backup if some node fails in FS. ES maintains some inactivated nodes with redundant information of the original data. Two different data redundancy technologies, replication and erasure coding, are considered in our work. We develop greedy failure recovery algorithms based on these two technologies. And according to analysis of the greedy algorithms, we propose a recovery aware data placement policy which can further improve the efficiency of failure recovery. To evaluate the energy efficiency of our algorithms, we build energy model and simulate node failure in clusters of different sizes.

The rest of this thesis is organized as follows: in Chapter 2, background information, including Hadoop Distributed File System (HDFS), Hadoop MapReduce and erasure coding are introduced and several related work are presented. Then, problem setting is given in

Chapter 3, after which, Chapter 4 characterizes two greedy algorithms: default replication based failure recovery algorithm and erasure coding based failure recovery algorithm. Our recovery aware data placement strategy is also described. Chapter 5 models the energy consumption of failure recovery for the two systems of different redundancy technologies. In Chapter 6, we use simulations to evaluate the two systems with and without recovery aware data placement strategy enabled. Finally, Chapter 7 and Chapter 8 summarize our work and propose the future work.

Chapter 2

Background and Related Work

One of the distinguished features of distributed system is the notion of partial failure [24]. A robust distributed system must be able to handle failure recovery automatically. In this Chapter, we start with introducing Hadoop Distributed File System (HDFS) and Hadoop MapReduce. Then, we describe and compare two commonly used data redundancy technologies: replication and erasure coding. Finally, we present some related research work.

2.1 Hadoop

Hadoop is a famous open-source framework that supports distributed processing of large-scale data sets across a cluster of computers [12]. Many large companies like Facebook, Yahoo!, and Amazon [10] are using Hadoop for processing big-data. Hadoop gains popularity because of its outstanding scalability and high fault tolerance. Specifically, comparing with traditional data center, Hadoop clusters have several advantages on data-intensive computing: 1) it implements MapReduce framework to simplify the parallelism of users' applications; 2) it uses commodity machines rather than high-budget servers to enhance scalability and flexibility; 3) it tolerates faults at different levels, including disks, nodes,

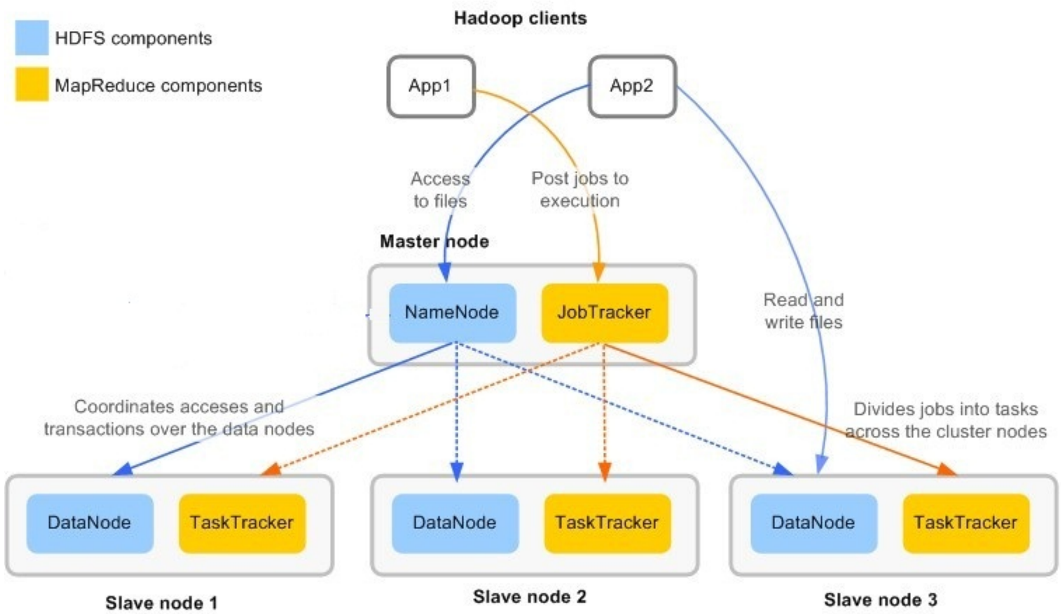


Figure 2.1: Hadoop Base Platform [8]

switches, networks, to improve the reliability. In this Chapter, we briefly describe the two subsystems in Hadoop base platform, i.e., Hadoop Distributed File System (HDFS) and Hadoop MapReduce [27]. Figure 2.1 depicts the collaboration between these two components.

2.1.1 Hadoop Distributed File System

Our work focuses on the data availability in Hadoop. It is thus necessary to first understand Hadoop distributed filesystem, HDFS. In this Chapter, we briefly introduce the architecture and then describe the fault tolerance and data placement policy in HDFS.

- Architecture

  Files stored in HDFS are divided into **blocks**. Each block unit is 64MB by default. With such a setting, a file can be very large since it can take advantage of all the disks in the cluster. This design also enhances the data scalability of Hadoop clus-

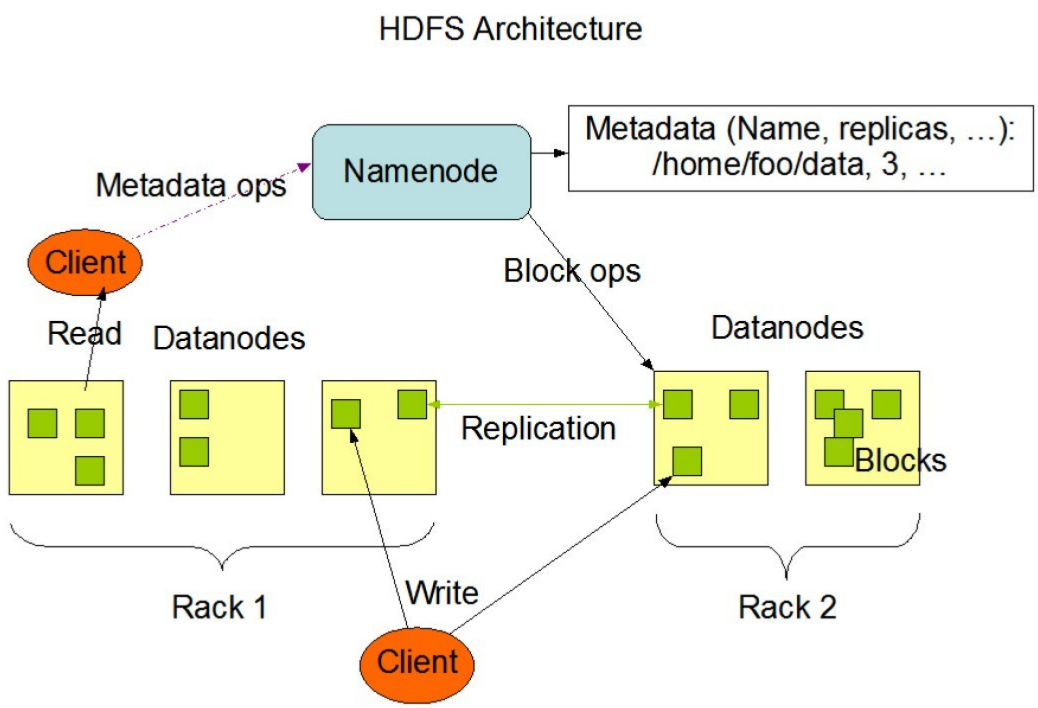


Figure 2.2: HDFS Architecture [27]

ters. As illustrated in Figure 2.2, Hadoop cluster follows master-slave architecture. In particular, there is a master node named **Namenode** with a number of slave nodes, called **Datanodes**. In the cluster, Namenode maintains the file system namespace and the metadata for all the files while the Datanodes store the blocks. Periodically, every Datanode sends a heartbeat and a report of block list periodically to the Namenode such that Namenode can construct and update the "blocksMap" (a mapping table which maps data blocks to Datanodes). Because Namenode has the data placement information of all Datanodes, it coordinates access operations between clients and Datanodes [8]. Finally, Datanodes are responsible for serving read and write requests.

- Fault tolerance and data placement policy

  Since block could be corrupted and machines or disks can fail, HDFS replicates each block to tolerate fault. Specifically, users can define **replication factor** when creating a file. This variable tells the system how many replicas are required. By default, every file has a same replication factor which equals three. That means three copies of each block are stored in HDFS. The placement of replicas follows a rack-aware placement policy. Generally speaking, Namenode selects a random Datanode in the cluster to place the first replica of a block, then it asks this Datanode copies the block to a different Datanode of the same rack. The block's third replica will be stored in a different rack. By storing two replicas in the same rack, this policy improves the write performance through reducing inter-rack write traffic. Figure 2.3 demonstrates an example of data placement. If the cluster only contains a single rack, three replicas of a block are randomly assigned to three different Datanodes.

2.1.2 Hadoop MapReduce

To process huge data sets within an acceptable amount of time, parallel-executable programs are demanded. However, developing such distributed programs are nontrivial and time consuming. For example, it is challenging to organize data and code, and handle failures for such programs. To simplify these tasks, an abstraction to organize parallelizable tasks, MapReduce, is developed. With MapReduce, programmers are only required to develop two functions: 1) Map( ) for data processing, and 2) Reduce( ) for collecting and digesting data. MapReduce takes care of nodes coordination, data transport, and failures.

As indicated by Figure 2.1, typically, each Hadoop node serves both as a storage node and a worker node. Hadoop MapReduce framework and Hadoop Distributed File System are running on the same set of nodes [11]. As HDFS, Hadoop MapReduce also works

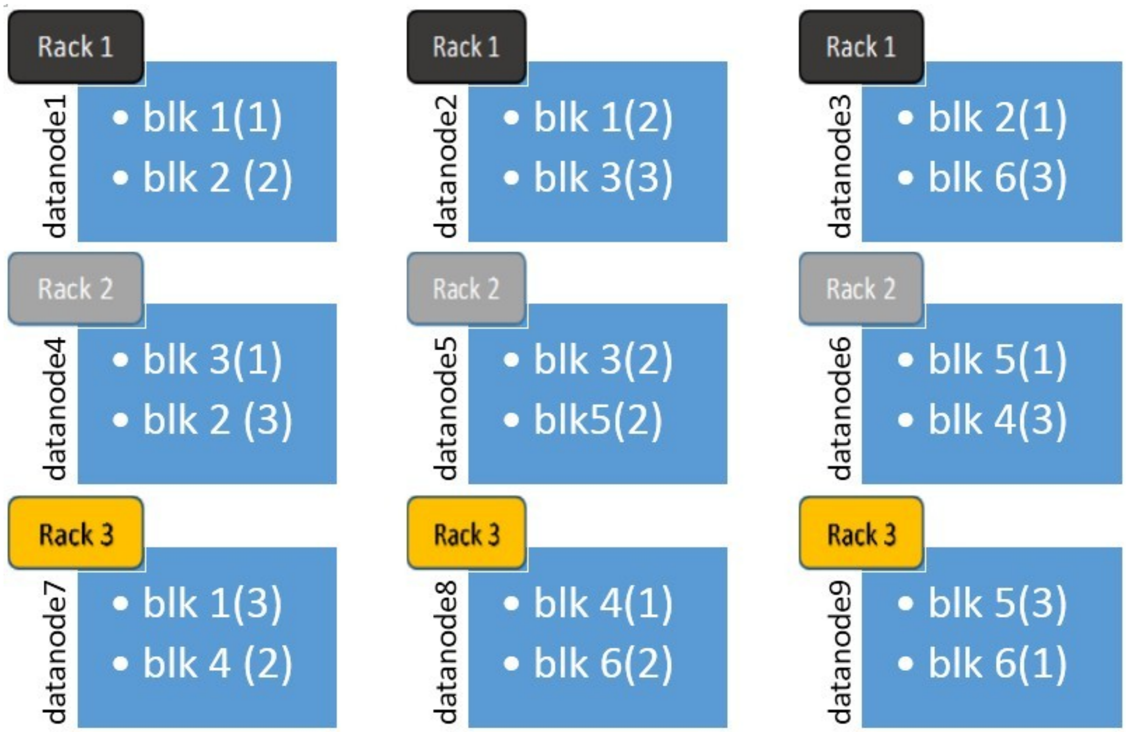


Figure 2.3: Data placement in HDFS

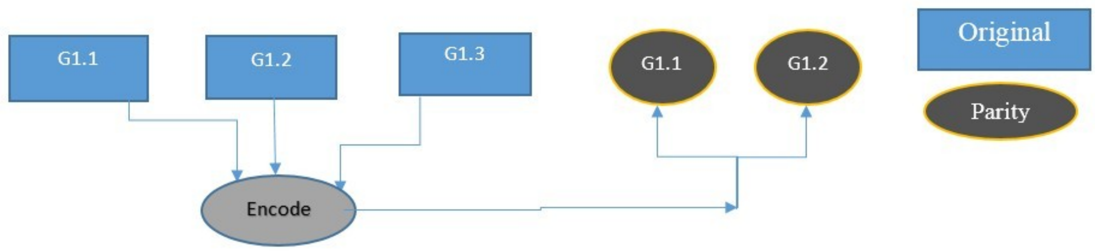
in master-slave mode. Specifically, there is a master node called **JobTracker** and many slave nodes called **TaskTrackers**. Jobs are submitted to JobTracker by clients. Based on the scheduling policy of Hadoop MapReduce, JobTracker assigns Map tasks and Reduce tasks to TaskTrackers. Map tasks are defined by Map( ) and Reduce tasks are defined by Reduce( ). A MapReduce job starts with parallelizing several Map tasks and running them on different TaskTrackers. After a certain number of Map tasks have been completed, Reduce tasks will be scheduled to run on TaskTrackers. Finally, results will be stored in HDFS. JobTracker monitors all the tasks and re-executes the failed tasks to guarantee fault tolerance [11].

2.2 Data Redundancy Technologies

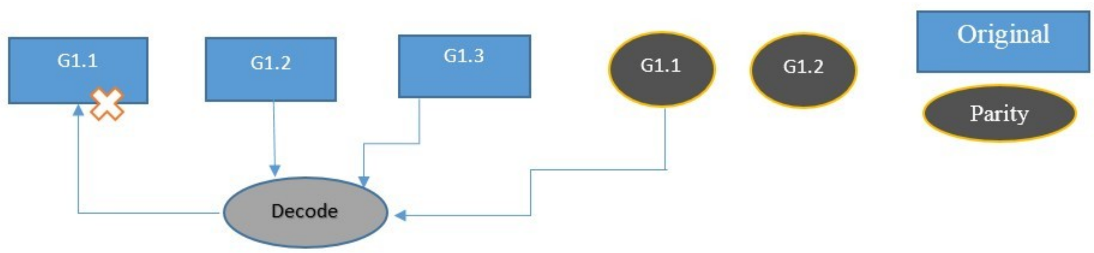
One of the biggest challenges in distributed systems like Hadoop is to guarantee the data durability even if some nodes fail. Thus, it is important to maintain redundancy for stored data in Hadoop. As mentioned in Chapter 2.1.1, replication is often employed in HDFS for achieving fault tolerance. Besides the replication method, another commonly-used data redundancy technology applied in distributed storage infrastructures is parity schema, i.e., erasure coding [1].

2.2.1 Erasure Coding

While replication technology provides redundancy by simply creating copies of original data, erasure coding technology encodes the data. Specifically, given an object, erasure coding system first divides it into d fragments, then produces another e fragments based on generator matrix [17], and these $d + e$ fragments are defined as an erasure coding set. $\frac{d}{d+e} < 1$ gives the encoding rate of the set. One of the most attractive features of erasure coding is that any d fragments in one set can be used for reconstructing the original d fragments. To maximize fault tolerance, fragments of a set are stored in different nodes. Figure 2.4 presents examples of encoding and decoding processes with $d = 3$ and $e = 2$. Erasure codes are a superset of replicated and RAID systems [26]. When $d = 1$ and $e = 2$, three replicas will be created for a block, which is the same as the replication. RAID 4 can be described as erasure coding with $d = 4$, $e = 1$, while RAID6 means $e = 2$. There are several open-source erasure coding methods and libraries, like LUBY, JERASURE and EVENODD [23].



(a) Encoding



(b) Decoding

Figure 2.4: Erasure coding with d=3 and e=2

2.2.2 Replication vs. Erasure Coding

With erasure coding technology, because any d out of d+e fragments can be used in reconstructing the original data, the system can tolerate the loss of up to e fragments with $\frac{d+e}{d}$ times storage space. However, if replication technology is used, $e+1$ times storage space is required in order to provide the same fault tolerance level e. Therefore, erasure coding has advantages in recovering failure and saving storage space. However, it is more complicated and requires some extra computation for encoding and decoding when compared with the replication technology.

2.3 Related Work

In order to minimize the power consumption of large data centers, much research on power provisioning of data centers have been conducted [2, 3, 6, 7, 9, 20, 21, 22]. A majority of work focus on developing scheduling algorithm to avoid low-utilized or idle machines. For example, [13] proposes a dynamic provisioning and scheduling algorithm that continually adjusts the number of active machines based on workload, and [20] develops an energy-conserving approach where the entire system transits rapidly between a high-performance active state and a near-zero-power idle state according to the instantaneous load.

Similar to traditional clusters, Hadoop clusters consume a plenty of energy for maintaining low-utilized or idle machines. But due to the complexity of Hadoop clusters, fewer research work on their power management have been published. Lang and Patel [15] develop a technique called All-In Strategy(AIS) which uses all the nodes in the cluster to run a workload and then turns off the entire cluster. However, running a workload in all Datanodes imposes unnecessary but significant data transfer. Besides, right workload may not have enough tasks to run on all Datanodes simultaneously. Thus, this technique is inefficient. A more interesting research, in our opinion, is by Leverich et al. [16] who develop a mechanism named “covering subset”. Basically, the nodes in a Hadoop cluster are grouped into two sets, covering subset and non-covering subset. Covering subset stores at least one replica of all data blocks such that nodes in non-covering subset can be turned off without affecting data integrity. However, they do not consider the data availability problem caused by node failure in covering subset. Our work adopts a concept similar to the “covering subset” and targets at the energy efficient failure recovery in that set.

Erasure coding technology is considered as an significant approach for maintaining data redundancy. And it is being applied to several well-known distributed storage systems [14] such as OceanStore [14] and HyFS [18]. Weatherspoon and Kubiatowicz [26] compare erasure coding versus replication in a quantitative way when building a distributed storage infrastructure. Specifically, they show that erasure coding based systems have a much larger mean time to failure than replication based systems with similar storage and bandwidth requirements. They also point out that erasure coding systems use much less bandwidth and storage to provide similar system durability as replication based systems.

The most closely related work to our thesis is [5]. In that paper, Fan et al. introduce DiskReduce which integrates RAID schemes into HDFS. Because they find most data accesses happen a short time after one block's creation, DiskReduce proposes a delayed encoding strategy which uses replication mechanism initially but then gradually converts the copies into erasure coded data. Unlike our objective of achieving energy efficient failure recovery, DiskReduce employs erasure coding to save storage space for data-intensive computing.

Chapter 3

Problem Setting

In this Chapter, we describe the system model and the research problem. Specifically, we define the terms in our work including Fundamental Set (FS), Extended Set (ES), and Waiting Set (WS).

3.1 System Model

We assume a homogenous Hadoop cluster, which is composed of a Namenode and a few Datanodes. As depicted in Figure 3.1, the Datanodes are grouped into three sets: *Fundamental Set (FS), Extended Set (ES), and Waiting Set (WS)*. FS is similar to the covering subset (CS) defined in [16] which stores only one copy of all data blocks. Redundant data blocks are generated following a redundancy mechanism, and they are stored in ES nodes. The size of ES, i.e., the number of Datanodes contained in ES, is proportional to that of FS and we store approximately the same number of blocks in each node of FS and ES. This is because a same amount of redundancy is maintained for every unique block. Datanodes in WS are not assigned to store any data and they are used as backup nodes for failure recovery. The size of WS is flexible and will not be discussed in this thesis. When there is

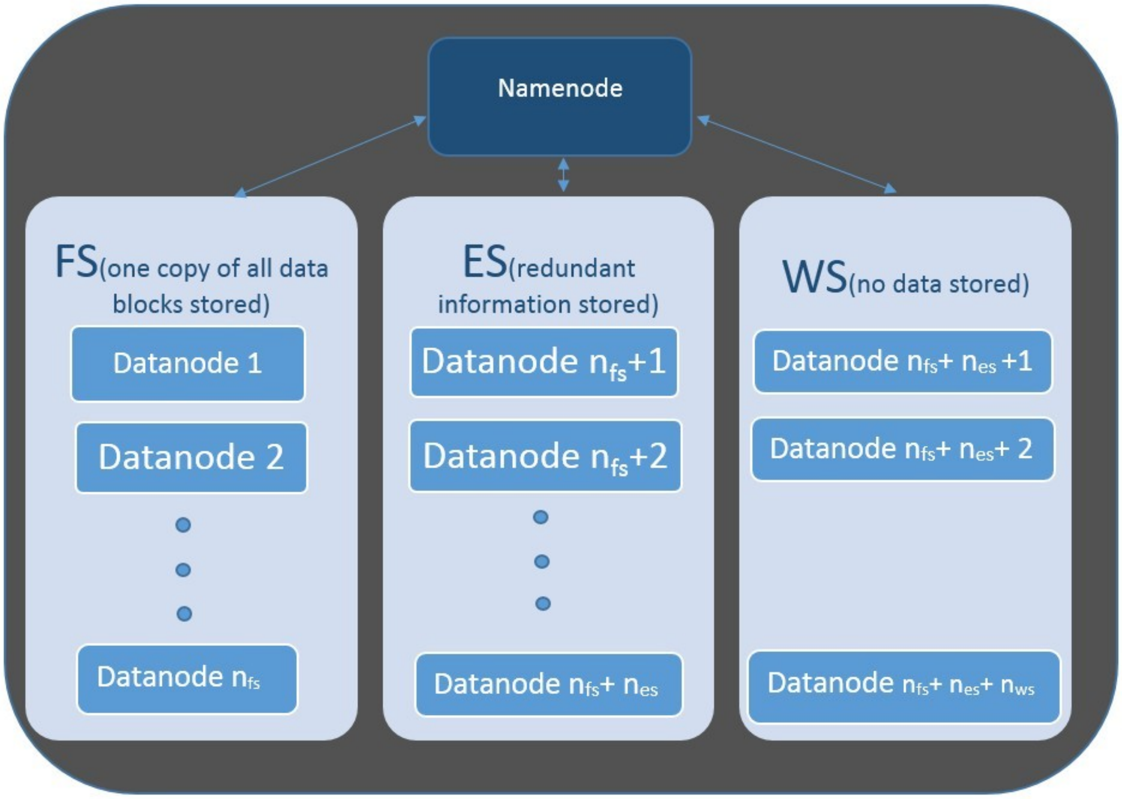


Figure 3.1: System Model

no node failure, only nodes in FS are required to be active all the time to respond to data requests while nodes in ES and WS can be turned off to save energy.

3.2 Node Failure and Recovery

In distributed systems, a node can become unaccessible when it experiences hardware/software errors. Usually, clusters of commodity machines have high failure rates. According to a trace of one Microsoft cluster with 1707 worker nodes, the Mean Time Between Failure (MTBF) is about 40 minutes. Hadoop clusters often consist of commodity computers. Therefore, nodes failure cannot be neglected in Hadoop clusters. In this thesis, we consider node crash failure happened in FS. In particular, we are interest in single node failure[1] since it contributes up to 90% of nodes failure in typical commodity clusters [**?**]. As mentioned, only one replica of all data blocks are stored in FS. When a FS node fails, data integrity is damaged. To restore the data availability, we activate a new node from WS to replace the failed node in FS. Specifically, we recover the lost data replicas by utilizing the redundant data stored in ES, and copy them to the newly activated WS node, which will then be moved to FS.

[1]Note that the failure recovery algorithms presented in Chapter 4 can be applied to recover multi-node failure, but the energy model we built in Chapter 5 is more towards single node failure.

Chapter 4

Failure Recovery Algorithms

As mentioned, node failures are common in large clusters. However, this problem has not been considered seriously when the covering subset mechanism was designed [16]. The system simply activates all nodes in non-covering subset to recover node failures. Since the process of starting up and turning off machines consumes high energy and causes wear and tear, this approach is definitely not optimal. In this thesis, we investigate and develop some energy efficient methods for restoring lost data. First and foremost, we develop a greedy failure recovery algorithm for the default replication-based Hadoop system to minimize the number of nodes to be activated in ES. Then, we integrate erasure coding technology into Hadoop to leverage its space-saving feature and to take advantage of its flexibility in failure recovery. A greedy failure recovery algorithm for this modified Hadoop system is developed as well. Finally, based on the analysis of these two algorithms, we design a recovery aware placement strategy which can further improve the energy efficiency of failure recovery.

4.1 Failure Recovery with Replication Based Extended Set

By default, in HDFS, replication approach is used for maintaining data redundancy. Accordingly, we first study the case where r copies of all data blocks are stored in ES nodes. As mentioned, we divide all the Datanodes into three sets, FS, ES, and WS, and the size of ES is proportional to that of FS. If a total number of m unique data blocks are stored in n FS nodes, then $r * m$ data blocks are maintained in $r * n$ ES nodes. In both FS and ES, data blocks are randomly distributed and stored and replicas of a data block are kept in different nodes. Thus, on average, a FS/ES node gets around $k = \frac{m}{n}$ data blocks.

When there is a FS node failure, only partial rather than all data blocks get lost. To restore a few blocks, it is unnecessary to activate all Datanodes in ES. In order to achieve an energy-efficient failure recovery, we desire to minimize the number of nodes to be turned on during the recovery process. This energy-efficient failure recovery reduces to the set covering problem because we need to identify the smallest number of sets (i.e., sets of data blocks in nodes) whose union contains all lost data blocks. Since the set covering problem is NP-hard, we develop a greedy algorithm to solve it. With this greedy failure recovery algorithm, one replica of each lost data block will be found and sent to a newly activated WS node for restoration. Algorithm 1 shows the details of the energy-efficient failure recovery algorithm when we employ replication as the redundancy technique in Extended Set. The algorithm uses a "compare" function to identify common blocks shared by two nodes. The *compare* function is as follows:

Function: **compare**

Input: 1.$a[m]$: an array that records data blocks stored in the failed node

2.$b[m]$: an array that records data blocks stored in an ES node

Output: $common\_blocks$: the number of common blocks of the two nodes

```
compare(boolean a[m], boolean b[m]){
    int common_blocks = 0;
    for(int i = 0; i < m-1; i++ )
        if(a[i] == TRUE && b[i] == TRUE)
                        ▷ The block exists in both node a and b
            common_blocks++;
    return common_blocks;
}
```

In Algorithm1, firstly, we record the lost data blocks in an array $failed\_node[\,]$ and then we calculate the number of unavailable data blocks ($lost\_blocks$) caused by the failure (lines 1-10). To recover the lost blocks, all unmarked ES nodes are examined to identify the node (indexed by max_row) that contains the largest number of replicas for lost data blocks (lines 12-23). That node is then marked and activated to send out the corresponding data copies ($common\_blockList$) (line 33). Specifically, the data copies are transferred to an activated node in WS. After the transmission, the activated ES node will be shut down automatically to save energy. This process continues until all lost blocks are recovered. $failed\_node[\,]$, $lost\_blocks$ are updated accordingly to reflect the blocks remained to be recovered (lines 24-32).

When a data block is lost, the probability of finding its replica in an ES node is:

$$p(replication) = \frac{r}{r * n} = \frac{1}{n} \tag{4.1}$$

Algorithm 1 Greedy Failure Recovery with Replication based Extended Set

Require: $dataFS[n][m]$: a two-dimensional boolean array that records the data placement information of the n Datanodes in FS, which can be got from $Namenode$. $dataFS[i]$ represents the data placement information of the **ith** node. If the **jth** block in is stored in the **ith** node, $dataFS[i][j] = TRUE$, otherwise $dataFS[i][j] = FALSE$.
Require: $dataES[r * n][m]$: similar to $dataFS$, $dataES$ records the data placement information of ES nodes.
Require: $failed$: the index of the failed node in FS, where $0 \leq failed < n$.

boolean $failed\_node[\,] = dataFS[failed]$
int $lost\_blocks = 0$
▷ *The number of unavailable data blocks*
List $common\_blockList$
▷ *The list of blocks that can be recovered by the selected node*
for $index = 0 \to m - 1$ **do**
    if $failed\_node[index] == TRUE$ **then**
        $lost\_blocks + +$
    end if
end for
Turn on a WS node
while $lost\_blocks! = 0$ **do**
    $common\_blocks = 0$
    $max\_row = 0$
    for $i = 0 \to r * n - 1$ **do**
        if the ith ES node is marked **then**
            Continue
        end if
        $result = compare(failed\_node, dataES[i])$
        if $result > common\_blocks$ **then**
            $common\_blocks = result$
            $max\_row = i$
        end if
    end for
    if $common\_blocks > 0$ **then**
        $lost\_blocks- = common\_blocks$
        $common\_blockList.empty()$

Algorithm 1 Greedy Failure Recovery with Replication based Extended Set (continued)

for $j = 0 \rightarrow m - 1$ **do**
  if $failed\_node[j] \&\& dataES[max\_row][j]$ **then**
    $failed\_node[j] = FALSE$
    ▷ *Update the information of lost data blocks*
    $common\_blockList.add(j)$
    ▷ *Record the list of blocks that can be recovered*
    Mark and activate the max_row -th ES node to send out blocks in its $common\_blockList$ to the WS node
    ▷ *Mark the node as used for recovery*
  end if
end for
end if
end while

This is because the r replicas of the block are randomly distributed and stored in the $r*n$ ES nodes. If we take the k lost data blocks into consideration, the probability of finding a large number of them in one node is small. Therefore, in order to recover from a node failure, quite a few ES nodes need to be turned on[1]. We believe such an inefficiency is caused by two reasons: 1) the "one-to-one" recovery model of replication, i.e., a data block can only be restored by its replica and 2) the random placement of data blocks in FS and ES. Therefore, in order to improve the similarity between two nodes, one possible approach is to change the "one-to-one" recovery model to "one-to-many" model and another is to develop a new data placement strategy as will be describe in Chapter 4.2 and Chapter4.3, respectively.

[1]The results in Chapter 6 also confirm this statement. In most cases, almost all nodes in ES are required to be turned on for restoring data blocks of a failed node.

4.2 Failure Recovery with Erasure-Coding-Based Extended Set

"One-to-many" recovery model means that a data block in ES has the ability to recover several different data blocks in FS. Definitely, this recovery model cannot be achieved when we use replication method for maintaining data redundancy. As described in Chapter 2.2.1, erasure coding mechanism has an outstanding flexibility in failure recovery. In an erasure coding set, any d out of $d + e$ fragments can be used to reconstruct the original d fragments. Hence, we integrate erasure coding approach into ES for enhancing the data recovery capability. In our system, files are divided into blocks and every randomly selected d blocks will be treated as one erasure coding object[2]. For each erasure coding object, e encoded blocks/fragments will be derived[3]. Since FS is kept online for serving data requests, the original d blocks from all erasure coding sets are put into FS while the encoded e blocks from all the sets are stored in ES. Similar to the replication approach, we make an assumption that n Datanodes with m unique data blocks are contained in FS. In addition, we assume data blocks in the range [$i*d$, $((i+1)*d-1)$], $i = 0, 1, \cdots, s-1$ are grouped into the ith erasure coding object. Hence, in total, we have $s = \lceil \frac{m}{d} \rceil$ erasure coding objects and sets[4]. Based on an encoding rate $\frac{d}{d+e}$, $e * \lceil \frac{m}{d} \rceil$ number of encoded blocks are stored in e*$\lceil \frac{n}{d} \rceil$ ES nodes. In both FS and ES, all blocks are randomly distributed while satisfying the following requirement: blocks of the same erasure coding set are stored in different nodes. Again, each node in FS and ES stores $k = \frac{m}{n}$ blockson average.

[2]Specifically, in our system, blocks of all files are put together and then divided into erasure coding object to reduce the unnecessary padding.

[3]In the rest of this thesis, "block" and "fragment" have the same meaning when we refer to the "erasure coding method" and they will be used interchangeably.

[4]In practice, we will set $\lim d \times s \to m^+$ to avoid unnecessary padding.

Basically, when a FS node fails, for each lost block, we need to find one encoded block in ES and other remaining $d-1$ original blocks to reconstruct the data[5]. The reconstructed data block will then be sent to a newly activated WS node. Specifically, approximately k blocks from k sets are lost when a node fails. Therefore, k erasure coding sets are required to be decoded for reconstructing the lost blocks. As described in [26], decoding an erasure coding set is computation-intensive and time-consuming. Because all Datanodes stop serving data requests till all lost blocks are recovered, it is obviously non-optimal to launch all the decoding tasks on one node. To be efficient, we parallelize the k decoding tasks on the $n-1$ remaining nodes of FS. That is, each FS node is assigned approximately $\frac{k}{n-1}$ decoding tasks. Since each set still has $d-1$ data blocks stored in FS, to reduce data transfer, a FS node with a block for a set will be chosen for reconstructing the set[6]. And the encoded blocks in ES will also be sent to the corresponding FS node. Similar to replication-based system, activating all ES Datanodes is unnecessary. To save energy, we also try to minimize the number of ES nodes to be activated during the recovery process. And this problem reduces to the set covering problem as well. In this setting, we need to identify the smallest number of sets (i.e., sets of erasure coding sets in nodes) whose union contains all lost erasure coding sets. Accordingly, a greedy failure recovery algorithm is proposed. Algorithm 2 presents how our greedy algorithm works by using ES nodes to recover a FS node failure.

The purpose of function *computeSetFailure* in Algorithm 2 is to identify the sets affected by the failure of a given FS node. Because with erasure coding approach, every block in the same set can be treated equally from the perspective of failure recovery. As a

[5]Because at most one block from one set can be stored in a node, a set can lost at most one block when a node fails. That is, $d-1$ original blocks are still available in FS

[6]Specifically, with the random distribution of data blocks in FS, each node is likely to hold $\frac{k*(d-1)}{n-1}$ blocks for the failed sets

result, we only care about the set rather than the exact block information. The *computeSet-Failure* goes as follow.

Function: **computeSetFailure**

Input: 1. $a[]$: an array that records data blocks stored in the failed node

2. set: total number of erasure coding sets

3. $block$: number of original fragments per erasure coding set, i.e., d.

Output:setLosted[ ]: an array that erasure coding sets contained in the failed node

```
computeSetFailure(boolean a[ ], int set, int block){
    boolean setLosted[set], sI = 0;
    for(sI = 0; sI < set-1; sI++){
        for(int bI = 0; bI < block; bI++)
            if(a[sI*block+bI] == TRUE){
                setLosted[sI]=TRUE;
                break;
            }
    }
    for(int i = (set-1)*block; i < n*k; i++){
        if(a[i] == TRUE){
            setLosted[sI] = TRUE;
        }
    }
        return setLosted;
}
```

Another function *nodeCompare* in Algorithm 2 is designed to compare the sets stored in two nodes. This function tells how much one node can help to recover the failure of another node. The description for *nodeCompare* is listed below.

Function: **nodeCompare**

Input: 1. set: total number of erasure coding sets

2. $n1[set]$: an array that records erasure coding sets contained in the failed node

3. $n2[set]$: an array that records erasure coding sets contained in an ES node

Output:1.$similarity$: the number of erasure coding sets that can be recovered

2.$lost$: an array that records erasure coding sets remained to be recovered

3.$recovered$: an array that records the recovered erasure coding sets

```
nodeCompare(int set, boolean n1[set], boolean n2[set]){
      int similarity = 0;
      List common_setList;
      boolean lost[set] = n1[set];
           ▷ Before recovery, lost contains all erasure coding
sets stored in node n1
      for(sI = 0; sI < set; sI++){
                          ▷ The similarity is derived set by set
           if(n1[sI]&n2[sI] == true){
                similarity ++;
                lost[sI] == false;
                common_setList.add(sI);
           }
      }
      return similarity, lost and common_setList;
  }
```

The idea of Algorithm 2 is similar to that of Algorithm 1. The only difference is that Algorithm 1 tackles the failure block by block while Algorithm 2 deals with the failure set by set. That is also why we develop function *computeSetFailure*. Basically, in Algorithm 2, the lost data blocks are first stored in an array $failed\_node[\,]$ and then the number of unavailable data blocks ($lost\_blocks$) caused by the failure is computed (lines 1-8). Instead of using the data block information directly, we convert the lost data blocks to the lost sets ($failed\_set$) by using function *computeSetFailure* (line 9). To recover the lost sets, all unmarked ES nodes are examined to identify their abilities in recovering the failure. The node with the maximum recovery capability (indexed by max_row) , that is, a node containing the largest number of fragments for lost sets, is selected (lines 10-25). That node is then marked and activated to send out the corresponding data blocks ($common\_setList$) for failure recovery (line 29) and $failed\_set[\ ]$, $lost\_blocks$ are updated accordingly to reflect the sets remained to be recovered (lines 26-31). Specifically, the blocks are sent to the $n-1$ remaining FS nodes. After the transmission, the activated ES node will be shut down automatically.

Besides an encoded block retrieved from an ES node and a local block, to decode an erasure coding set, a FS node still needs to get $d-2$ original blocks from other FS nodes. Note that a decoding task can only be started after d blocks of a set have been received. Therefore, we transfer data blocks following their set order. Since decoding is computation-intensive and data transfer is network-intensive, to be efficient, we launch them simultaneously whenever possible. After all lost sets are decoded, the reconstructed data blocks will be sent to a newly activated WS node.

The probability of recovering one lost data block in FS by a random node in ES is:

$$p(erasure\_coding) = \frac{e}{e * \frac{n}{d}} = \frac{d}{n} = d * p(replication) \tag{4.2}$$

That is, $p(erasure\_coding)$ is d times of $p(replication)$. This is because in an erasure coding set, one encoded block can be used to recover any one of the d original blocks. Thus, a fewer number of machines are turned on to tackle a node failure. However, it is important to notice that this smaller number of active nodes does not necessarily guarantee energy-efficient failure recovery. While the erasure coding based approach requires a fewer number of machines to be turned on for failure recovery, it requires extra computation and data transfer for reconstructing lost data blocks. In order to compare energy efficiency of failure recovery in these two systems, we build energy model and give analysis in Chapter 5.

4.3 Recovery Aware Data Placement Strategy

The incentive of the greedy failure recovery algorithms is to minimize the number of nodes required to be activated during the recovery process. However, the simulation results[7] show that the greedy algorithms are inefficient and a large proportion of machines are always required in order to recover a FS node failure. Basically, more than $\frac{1}{r}$ of ES nodes are demanded when we use replication-based system, and more than $\frac{1}{e}$ of ES nodes are required if erasure-coding-based system is employed. Mathematic analysis also justifies and proves the correctness of the simulation results. Specifically, when erasure-coding-based ES is used, approximately k blocks from k sets are lost if a FS node fails. Suppose $f(x)$ data blocks can be recovered in the xth ($x > 0$) attempt by applying the greedy failure recovery algorithm (refer to Chapter 4.2, based on the definition of greedy algorithm, we have $f(x) \geq f(x+1) > 0$. For a given failure, we define the number of sets recovered by an ES node as its recovery capability. Hence, $f(x)$ also represents the recovery capability of the node used by the greedy algorithm in the xth iteration. Assume $F(p) = \sum_{i=1}^{p} f(i)$, in which $p \geq 1$ and $F(0) = 0$, and if a total of X steps are required to deal with a node failure, $F(X) = k$. As a characteristic of greedy algorithm, solution at each step is at least as good as the average. Hence, in the ath attempt, the number of erasure coding sets recovered will be no less than the average, i.e.,

$$f(a) \geq \frac{e * \sharp unrecovered\_sets}{unmarked\_ES\_nodes} = \frac{e * (k - F(a-1))}{\frac{e*n}{d} - (a-1)} \qquad (4.3)$$

[7]Refers to Table 6.2 and Table 6.5, the results are discussed in detail in Chapter 6

where $a \geq 1$. However, since random distribution is used for placing data blocks, the sets that can be recovered by each ES node is approximately the same. That is,

$$f(a) = \frac{e * (k - F(a-1))}{\frac{e*n}{d} - (a-1)} \tag{4.4}$$

Thus, at the first attempt,

$$f(1) = \frac{e * k}{\frac{e*n}{d}} = \frac{k * d}{n} \tag{4.5}$$

blocks can be restored. As discussed, $f(x)$ is a monotonically decreasing function. Accordingly, $X \geq \frac{k}{f(1)} = \frac{n}{d}$, that is, at least $\frac{n}{d}$ nodes in ES are required to be turned on for recovering a node failure in FS. Intuitively, since every Datanode in ES has a nearly same recovery capability, we expect that every other nodes used in the following steps can recover $\frac{k*d}{n}$ sets as well. Then, approximate $\frac{n}{d}$ ES nodes can recover a FS node failure. However, further analysis refutes this statement. Consider the second recovery attempt in the system,

$$\begin{aligned} f(2) &= \frac{e * (k - \frac{k*d}{n})}{\frac{e*n}{d} - 1} \\ &= \frac{k * d * e * (n-d)}{n * (e * n - d)} \\ &= \frac{k * d}{n} * \frac{e * n - e * d}{e * n - d} \\ &= f(1) * \frac{e * n - e * d}{e * n - d} < f(1) \end{aligned} \tag{4.6}$$

It shows that the second attempt recovers a significant fewer number of sets when compared with the first attempt. Similarly, we can derive $f(x) > f(x+1)$. This indicates that the recovery capability of unmarked nodes decrease as the recovery progresses. The reason is that marked nodes and unmarked nodes have overlap on the lost sets. Consider the moment when the ath attempt finishes but the $(a+1)$th attempt has not started yet, and $a + 1 \leq X$.

There has been $F(a)$ sets recovered until the ath attempt. The probability of finding at least one of the $F(a)$ recovered sets in an unmarked FS node is:

$$probility = \begin{cases} 1 & \text{if } \frac{m}{d} - F(a) < k \\ 1 - \dfrac{\begin{pmatrix} \frac{m}{d} - F(a) \\ k \end{pmatrix} * e^k}{\sum_{i=0}^{min(k,F(a))} \begin{pmatrix} F(a) \\ i \end{pmatrix} \begin{pmatrix} \frac{m}{d} - F(a) \\ k-i \end{pmatrix} * (e-1)^i * e^{k-i}} & \text{if } \frac{m}{d} - F(a) \geq k \end{cases} \tag{4.7}$$

Firstly, because every node is assigned approximate k sets, if no more than k sets left when we deduct $F(a)$ recovered sets from the total number of sets $\frac{m}{d}$, each unmarked node stores at least one fragment for failed set that is common as the recovered $F(a)$ sets. Accurately, at least $k - (\frac{m}{d} - F(a))$ recovered sets are contained in every unmarked ES node. While if there are more than k sets left, the probability of finding an unmarked node which does not contain any of the $F(a)$ recovered sets is:

$$\frac{\begin{pmatrix} \frac{n*k}{d} - F(a) \\ k \end{pmatrix} * e^k}{\sum_{i=0}^{min(k,F(a))} \begin{pmatrix} F(a) \\ i \end{pmatrix} \begin{pmatrix} \frac{n*k}{d} - F(a) \\ k-i \end{pmatrix} * (e-1)^i * e^{k-i}} \tag{4.8}$$

This probability is very small since the numerator is just a small component of the denominator. Therefore, the corresponding probability of finding at least one set that is already recovered in an unmarked ES node is very large. As a result, the recovery capability of an unmarked node declines. Moreover, if the probability in equation (4.7) is larger, the recovery capability of an unmarked node is likely to decrease more sharply. Hence, the inherent similarity of any two ES nodes largely harms the efficiency of the greedy algorithm.

When a FS node fails, approximately k blocks from k sets are lost. Ideally, we expect that the algorithm could select X nodes with non-overlapping sets. That is, the X selected nodes contain only one fragment for each failed set. However, this objective is nontrivial because the specific sets involved in a failure are unpredictable. N node fails randomly and any k out of $\frac{m}{d}$ sets could get lost. Fortunately, only one fragment per set is lost when a node fails. Accordingly, a collection that contains one fragment for each set can be regarded as the covering set for a node failure. Thus, we group one fragment from every set together to form a unit. Specifically, we divide ES nodes into e equal partitions. Each set stores one fragment in a partition. Hence, the lost k sets can be found in any of the e partitions while any two ES nodes in a partition do not have any overlapping sets. In the worst case, a node failure in FS can be recovered by $\frac{1}{e} * \frac{e*n}{d} = \frac{n}{d}$ number of nodes. Therefore, $X \leq \frac{n}{d}$. Note that replication can be treated as a special case of erasure coding where $d = 1$ and $e = 2$. With the greedy algorithm presented in Chapter 4.1, at least n nodes are demanded for recovering a FS node failure. To improve the efficiency, we can also apply a similar recovery aware data placement strategy in the replication-based system. Likewise, the replication based ES is partitioned into r parts since r replicas are maintained in ES. One replica of each data block is stored in a partition. Therefore, at most n nodes will be required for tackling a FS node failure.

There are also other data placement strategies that can improve the similarity between FS and ES nodes and thus lead to a smaller number of node activation. However, they are often too constrained to be applied. For example, in replication-based system, one intuitive idea is to maintain r mirrored nodes for a FS node in ES. In other words, each ES partition is a clone of FS. As a result, in every partition, we are able to find a mirrored Datanode for any failed FS node. However, such a mechanism is not feasible. Specifically, the data placement in FS is often changing dynamically in order to meet various requirements such as achieving workload balance. We need to keep ES nodes online to follow the data placement change of FS nodes. This violates the energy saving requirement. In this thesis, we thus have developed a much less constracined recovery-aware data placement strategy.

Algorithm 2 Greedy Failure Recovery with Erasure-Coding-Based Extended Set

Require: $dataFS[n][m]$: a two-dimensional array that records the data placement information of the n Datanodes in FS, which can be got from $Namenode$. $dataFS[i]$ represents the data placement information of the **ith** node. If the **jth** block in is stored in the **ith** node, $dataFS[i][j] = TRUE$, otherwise $dataFS[i][j] = FALSE$.
Require: $failed$: the index of the failed node in FS, where $0 \leq failed < n$.
Require: d : the number of original fragments per erasure coding set
Require: e : the number of encoded fragments generated per erasure coding set
Require: $dataES[\lceil (e * n/d) \rceil][\lceil m/d \rceil]$: a boolean two-dimensional array that records the set placement information of the $\lceil (e * n/d) \rceil$ Datanodes in ES, which can be obtained from the metadata in $Namenode$. $dataES[i]$ gives the set placement information of the **ith** node. If one fragment of the **jth** set is stored in the ith node, $dataES[i][j] = TRUE$; otherwise $dataES[i][j] = FALSE$.

int $total\_set = \lceil m/d \rceil$
boolean $failed\_node[\,] = dataFS[failed]$
int $lost\_blocks = 0$
for int $index = 0$; $index < m$; $index++$ **do**
    if $failed\_node[index] == TRUE$ **then**
        $lost\_blocks++$
    end if
end for
boolean $failed\_set[total\_set] = computeSetFailure(failed\_node, total\_set, d)$
while $lost\_blocks! = 0$ **do**
    $common\_sets = 0$
    $max\_row = 0$
    $common\_setList.empty()$
    for $i = 0 \rightarrow e * n/d$ **do**
        if the ith ES node is marked **then**
            Continue
        end if
        $result$ = $nodeCompare(total\_set, failed\_set, dataES[i])$
        if $result.similarity > common\_sets$ **then**
            $common\_sets = result.similarity$
            $max\_row = i$
            $unrecovered = result.lost$
            $common\_setList = result.common\_setList$
        end if
    end for

Algorithm 2 Greedy Failure Recovery with Erasure-Coding-Based Extended Set(continued)

```
    if common_sets > 0 then
        lost_blocks −= common_sets
        failed_set = unrecovered
        Mark and activate the max_row th node of ES to send out encoded fragments in specified common_setList to the corresponding FS nodes
                                                            ▷ Mark the node as used for recovery
    end if
end while
```

Chapter 5

Energy Model

In this Chapter, we build the energy model for analyzing the energy requirement of failure recovery.

Before discussing the energy consumption of the failure recovery process, it is necessary to mention that we assume that the system serves data request only when all data are available in FS. In other words, if a node fails, no data request will be served during the failure recovery process. When a node fails in FS, based on the failure recovery algorithms we introduced in Chapter 4, we know the set of ES machines that need to be turned on for the failure recovery. Besides powering up these ES nodes, some extra work is required to restore the lost data. Specifically, nodes could be involved in sending/receiving data, or decoding data if the erasure coding approach is applied. Because we assume a homogenous cluster the power consumed by any two nodes to do the same task are supposed to be the same. In our system, possible tasks include data transfer (i.e., sending/receiving data blocks[1]), decoding (i.e., reconstructing the data) and both, whose power consumption are denoted as P_{tran}, P_{comp}, and P_{t+c}, respectively. Moreover, the energy and time spent by a node during the activation (inactivation) process is represented by E_{act} and T_{act} (E_{inact} and

[1] In order to simplify the analysis, we assume sending and receiving the same amount of data consume the same amount of energy.

T_{inact}). Additionally, P_{idle} represents the power consumption of an idle machine. Since our cluster consists of FS, ES and WS and the recovery process starts with retrieving data from ES and ends with receiving data in WS, we discuss the energy consumption of two failure recovery algorithms by analyzing energy spent in ES, FS and WS ($E(ES)$, $E(FS)$, and $E(WS)$) during the recovery processes.

5.1 Energy spent in ES

In ES, a set of nodes derived by the failure recovery algorithms will be turned on to send out data blocks for recovering lost data, and these nodes will be turned off immediately after the transmission. We assume every activated node in ES spends the same amount of energy during the recovery process. Suppose A nodes are required to be activated and each node spends T_{ES} seconds in sending out blocks[2]. Then, the energy consumed in ES can be described as:

$$E(ES) = A * (E_{act} + P_{tran} * T_{ES} + E_{inact}) \tag{5.1}$$

In formula (5.1), $E_{act} + P_{tran} * T_{ES} + E_{inact}$ stands for the total energy consumed by an ES node during the failure recovery.

- **For replication-based system:**

  When replication is used in ES, the data blocks will be directly transferred from ES nodes to a WS node. As a result, data transfer speed is limited by the receiving capability of the WS node rather than the aggregated sending capability of ES nodes. That is, we need $T_{ES} = T_{WS} = \frac{64*k}{b}$ (seconds) to transfer data, where 64 (MB) is the data block size and b (MB/s) gives a machine's network I/O bandwidth.

[2] Subscripts SR and EC will be added when we refer to the replication-based and erasure-coding-based systems. And this notation also applies to other parameters that will be used in this thesis.

Consequently, formula (5.1) becomes:

$$E(ES)_{SR} = A_{SR} * (E_{act} + P_{tran} * \frac{64 * k}{b} + E_{inact}) \tag{5.2}$$

- **For erasure-coding-based system:**

  Unlike replication-based system, in which data collected from ES can be used directly, some extra decoding work is required in the erasure-coding-based system. In order to reconstruct an original data object, d blocks need to be retrieved for an erasure coding set. Due to a FS node failure, we need to recover approximately k erasure coding data objects/sets. For each set, there are still $d-1$ blocks in FS and thus one more block needs to be retrieved from an ES node. Totally, approximately k blocks sent from A_{EC} ES nodes are needed in reconstructing the k lost data blocks. On average, an activated EC node sends out $\frac{k}{A_{EC}}$ blocks to FS nodes. As mentioned, in order to minimize the decoding time and maximize the utilization of active machines, we use the $n-1$ FS machines to reconstruct the k sets in parallel. Each machine will be assigned $\frac{k}{n-1}$ number of sets to reconstruct. Thus, $\frac{k}{n-1}$ ES blocks are received per node in FS. If $\frac{k}{A_{EC}} \geq \frac{k}{n-1}$, i.e., $A_{EC} < n-1$, the data transfer speed is limited by the aggregated sending capability of the A_{EC} ES nodes. That is, $T_{ES} = T_{FS1} = \frac{64 * \frac{k}{A_{EC}}}{b} = \frac{64 * k}{A_{EC} * b}$ (seconds)[3]; Otherwise, the data transfer speed is limited by the aggregated receiving capability of $n-1$ FS nodes. That is, $T_{ES} = T_{FS1} = \frac{64 * \frac{k}{n-1}}{b} = \frac{64 * k}{(n-1) * b}$ (seconds). As a result, formula (5.1) become:

$$E(ES)_{EC} = A_{EC} * (E_{act} + P_{tran} * \frac{64 * k}{min(A_{EC}, (n-1)) * b} + E_{inact}) \tag{5.3}$$

[3]This is a more common situation. Since ES contains totally $n * \frac{e}{d}$ and it is often the case that $d \geq e$, there is often less than n number of ES nodes and A_{EC} is likely to be the less than $n-1$.

5.2 Energy spent in FS

The energy consumed by FS nodes largely depends on the redundancy technology we used in ES. If replication approach is employed, all active FS nodes are simply kept idle waiting for the recovery process to complete. While if the erasure coding approach is applied, nodes in FS are involved in data transfer and decoding, as mentioned in Chapter 4.2.

$$E(FS) = (n-1) * (P_{idle} * T_{idle} + E_{tran} + E_{t+c} + E_{comp}) \tag{5.4}$$

where E_{comp}, E_{t+c}, and E_{tran} stand for energy devoured by a FS node in decoding only, data transfer and decoding in parallel, and data transfer only, respectively.

- **For replication-based system:**

  In replication-based system, FS nodes are not involved in a failure recovery. However, they still consume energy because the $n-1$ nodes are kept active during the process. They wait for $T_{act} + \frac{64*k}{b}$ seconds when ES nodes are activated and data are transferred from ES nodes to a WS node. Thus, the energy consumed by FS nodes is:

  $$E(FS)_{SR} = (n-1) * (P_{idle} * (T_{act} + \frac{64*k}{b})) \tag{5.5}$$

- **For erasure-coding-based system:**

  It is a bit more complicated to analyze energy consumed by FS nodes in an erasure-coding based system, since lost data blocks need to be recomputed in FS nodes. When a FS node fails, approximately k blocks from k different erasure coding sets are lost. To be efficient, these k sets will be reconstructed by the $n-1$ FS nodes in parallel. That is, each FS node reconstructs about $\frac{k}{n-1}$ sets. Since each of the k sets still has $d-1$ blocks stored in FS nodes, to reduce data transfer, a FS node with a block for a set will be chosen for reconstructing the set. A FS node will get $d-2$ blocks from other FS nodes and a block from an ES node, and then reconstruct the set using the d blocks. To start with, blocks from ES nodes are transferred to destination FS nodes. Specifically, a FS node first waits for powering up ES nodes and receiving data from them. It idle waits for T_{act} seconds, and then spends $T_{FS1} = \frac{64*k}{min(A_{EC},(n-1))*b}$ (seconds) in accepting $\frac{k}{n-1}$ data blocks from ES nodes. Hence, the energy consumption of a FS node during this stage is $P_{idle} * T_{act} + P_{tran} * \frac{64*k}{min(A_{EC},(n-1))*b}$ (J). In the next stage, a FS node retrieves the $d-2$ blocks from other FS nodes to decode a set. Each FS node sends and receives approximately $\frac{k}{n-1} * (d-2)$ number of blocks. Because the network interface card (NIC) can work in full duplex nowadays, sending and receiving data can be processed simultaneously without affecting each other. Thus, the time in transferring data within FS is $\frac{64*\frac{k}{n-1}*(d-2)}{b}$ (seconds) in total and $T_{tran} = \frac{64*(d-2)}{b}$ (seconds) per set. As discussed in Chapter 4.2, data transfer and decoding are launched simultaneously whenever possible. And data blocks are transferred following their set order. After receiving all blocks of the first erasure coding set, a FS node starts decoding that set while receiving blocks for the second set. Suppose the decoding time is T_{comp} per set. There could be two scenarios as characterized in Figure 5.1.

(a) When $T_{tran} \geq T_{comp}$, data transfer and decoding can overlap for $T_{comp} * (\frac{k}{n-1} - 1)$ seconds when decoding all but the last set. A FS node spends $T_{tran} + (T_{tran} - T_{comp}) * (\frac{k}{n-1} - 1)$ = $T_{comp} + (T_{tran} - T_{comp}) * \frac{k}{n-1}$ seconds exclusively in data transfer and T_{comp} seconds exclusively in decoding. Thus, the energy consumed by a FS node in this process is:

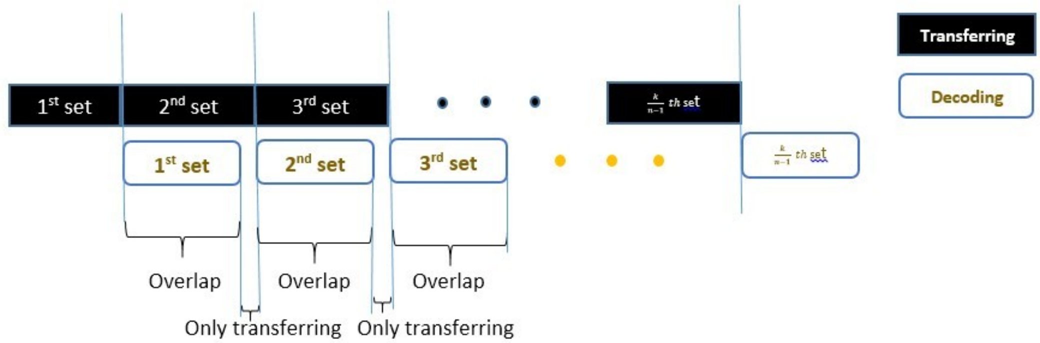
$$\begin{aligned}
&E_{tran} + E_{t+c} + E_{comp} \\
&= P_{tran} * (T_{comp} + (T_{tran} - T_{comp}) * \frac{k}{n-1}) \\
&+ P_{t+c} * (T_{comp} * (\frac{k}{n-1} - 1)) + P_{comp} * T_{comp}
\end{aligned} \tag{5.6}$$

(b) When $T_{tran} < T_{comp}$, data transfer and decoding can overlap for $T_{tran} * (\frac{k}{n-1} - 1)$ seconds when transferring all but the first set. A FS node also spends $(T_{comp} - T_{tran}) * (\frac{k}{n-1} - 1) + T_{comp}$ = $T_{tran} + (T_{comp} - T_{tran}) * \frac{k}{n-1}$ seconds exclusively in decoding and T_{tran} seconds exclusively in data transfer. Therefore, the energy consumed by a FS node in this process is:

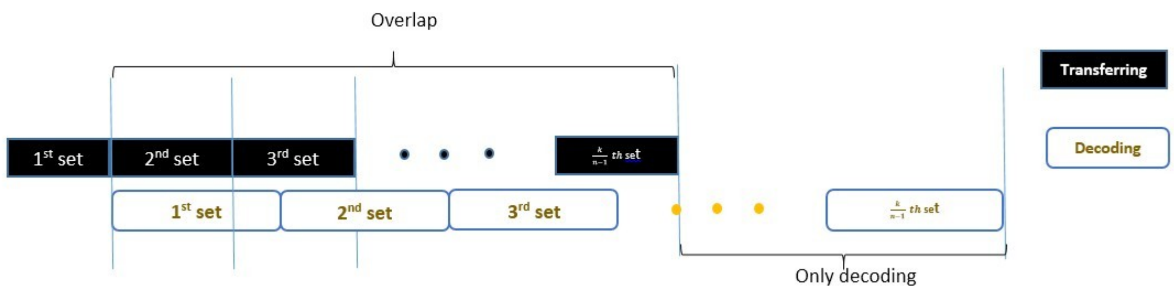
$$\begin{aligned}
&E_{tran} + E_{t+c} + E_{comp} \\
&= P_{tran} * T_{tran} \\
&+ P_{t+c} * (T_{tran} * (\frac{k}{n-1} - 1)) \\
&+ P_{comp} * (T_{tran} + (T_{comp} - T_{tran}) * \frac{k}{n-1})
\end{aligned} \tag{5.7}$$

After completing the decoding, the $n-1$ FS nodes send reconstructed k blocks to a WS node. The data transfer time relys on the receiving capability of the WS node. Thus, $T_{FS2} = T_{WS} = \frac{64*k}{b}$ seconds. The energy cost during this period is: $P_{tran} * \frac{64*k}{b}$.

Eventually, we expand the formula (5.4) as follow:



(a) $T_{tran} \geq T_{comp}$



(b) $T_{tran} < T_{comp}$

Figure 5.1: Decoding and data transfer in a FS node

$$E(FS)_{EC} = \begin{cases} (n-1) * (P_{idle} * T_{act} + P_{tran} * (\frac{64*k}{b} + \frac{64*k}{min(A_{EC},(n-1))*b} \\ +(T_{tran} - T_{comp}) * \frac{k}{n-1} + T_{comp}) + P_{t+c} * T_{comp} \\ * \frac{k-n+1}{n-1} + P_{comp} * T_{comp}) & \text{if } T_{tran} \geq T_{comp} \\ (n-1) * (P_{idle} * T_{act} + P_{tran} * (\frac{64*k}{b} + \frac{64*k}{min(A_{EC},(n-1))*b} \\ +T_{tran}) + P_{t+c} * T_{tran} * \frac{k-n+1}{n-1} + \\ P_{comp} * ((T_{comp} - T_{tran}) * \frac{k}{n-1} + T_{tran})) & \text{if } T_{tran} < T_{comp} \end{cases} \tag{5.8}$$

where $T_{tran} = \frac{64*(d-2)}{b}$ (seconds) is the time in transferring a set's data within FS nodes and T_{comp} is the time in decoding an erasure coding set.

5.3 Energy spent in WS

WS is designed as a backup for FS. When there is a failure in FS, we activate a WS node to join FS and to replace the failed node. In the replication based system, data blocks are copied from ES nodes to the WS node, while in the erasure-coding-based system, data blocks first are reconstructed in FS nodes and then transferred to the WS node. Nevertheless, the time spent in transferring data to the WS node are the same in both cases, i.e., $\frac{64*k}{b}$ (seconds). Hence, we get:

$$\begin{aligned} E(WS) &= E(WS)_{SR} = E(WS)_{EC} \\ &= E_{act} + P_{tran} * \frac{64*k}{b} \end{aligned} \tag{5.9}$$

5.4 Energy Consumption of the Two Approaches

Based on our analysis in Chapter 4, we know $A_{EC} \ll A_{SR}$, i.e., a smaller number of ES nodes need to be turned on in the erasure-coding based system. Thus, the erasure coding based system consumes less energy in ES for the failure recovery (see Equations (5.2) and (5.3)). However, unlike replication-based system in which data can be used directly, erasure coding requires extra computation in FS nodes. Therefore, erasure-coding-based system consumes more energy in FS (see Equations (5.5) and (5.8)). Put Equations (5.1)$\sim$(5.9) together, the total energy consumption for the failure recovery in the two systems are:

$$
\begin{aligned}
E_{SR} &= E(ES)_{SR} + E(FS)_{SR} + E(WS)_{SR} \\
&= A_{SR} * (E_{act} + P_{tran} * \frac{64 * k}{b} + E_{inact}) \\
&+ (n-1) * (P_{idle} * (\frac{64 * k}{b} + T_{act})) \\
&+ E_{act} + P_{tran} * \frac{64 * k}{b} \\
&= (A_{SR} + 1) * (E_{act} + P_{tran} * (\frac{64 * k}{b})) \\
&+ A_{SR} * E_{inact} + (n-1) * P_{idle} * (\frac{64 * k}{b} + T_{act})
\end{aligned} \tag{5.10}
$$

$$
\begin{aligned}
E_{EC} &= E(ES)_{EC} + E(FS)_{EC} + E(WS)_{EC} \\
&= A_{EC} * (E_{act} + P_{tran} * \frac{64 * k}{min(A_{EC}, (n-1)) * b} + E_{inact}) \\
&+ E(FS)_{EC} + E_{act} + P_{tran} * \frac{64 * k}{b} \\
&= (A_{EC} + 1) * E_{act} + 2 * P_{tran} * (\frac{64 * k * A_{EC}}{min(A_{EC}, (n-1)) * b})) \\
&+ A_{EC} * E_{inact} + E(FS)_{EC}
\end{aligned} \tag{5.11}
$$

where $E(FS)_{EC}$ is given in Equation (5.8).

Chapter 6

Simulation

In this chapter, we compare the replication-based recovery algorithm with the erasure-coding-based recovery algorithm via simulating a node failure in FS. We profile our local cluster, $Bugeater2$, to estimate the energy consumption of the two methods with/without our recovery aware data placement strategy plugged in.

6.1 Energy consumption

In Chapter 5, we analyzed and modeled the energy consumption for failure recovery. To get the parameters for the model and estimate the energy cost, we use and profile our testbed cluster, $Bugeater2$. In Bugeater2, every node has two AMD Opteron(tm) Processors 248 (2.2GHz, 64bit), 4GB Memory and one 80GB SATA disk. The speed of the switch that connects these nodes is 1Gbps. We use a Server Tech CWG-CDU power distribution unit (PDU) to measure the energy consumption. The energy consumed to boot up a machine is $24650Joule$, that is, $E_{act} = 24650J$, while the energy consumed to shut down a machine is very small and can be ignored, hence, we set $E_{inact} = 0J$. When a machine is idle, it consumes $70J$ per second, i.e., $P_{idle} = 70J/s$ while it consumes $90J$ per second if the machine is busy in decoding, that is, $P_{comp} = 90J/s$. Based on our measurements, the extra energy consumed in data transfer is negligible. Thus, we set $P_{tran} = P_{idle} = 70J/s$ and $P_{t+c} = P_{comp} = 90J/s$. The time spent in activating a machine in Bugeater2 is about 30 seconds, i.e. $T_{act} = 30s$. Moreover, although the ethernet is supposed to be 1Gbps = 128MB/s, but only $35MB/s$ can be achieved in practice. Thus, we set $b = 35MB/s$. Plugging in these parameters, Equations (5.10) and 5.11 become:

$$\begin{aligned} E_{SR} &= (A_{SR}+1) * (24650 + 70 * (\frac{64 * k}{35})) \\ &+ A_{SR} * E_{inact} + (n-1) * 70 * (\frac{64 * k}{35} + 30) \\ &= (A_{SR}+1) * (24650 + 128 * k) \\ &+ (n-1) * (128k + 2100) \end{aligned} \tag{6.1}$$

$$E_{EC} = \begin{cases} (A_{EC}+1) * 24650 + 256 * k * \frac{A_{EC}}{min(A_{EC},(n-1))} + (n-1) \\ *(2100 + 128 * \frac{k*(min(A_{EC},(n-1))+1)}{min(A_{EC},(n-1))} + 70 * T_{tran} \\ *\frac{k}{n-1} + T_{comp} * (70 + 20 * \frac{k}{n-1})) \\ & \text{if } T_{tran} \geq T_{comp} \\ (A_{EC}+1) * 24650 + 256 * k * \frac{A_{EC}}{min(A_{EC},(n-1))} + (n-1) \\ *(2100 + 128 * \frac{k*(min(A_{EC},(n-1))+1)}{min(A_{EC},(n-1))} + 160 * T_{tran} \\ +90 * T_{comp} * \frac{k}{n-1}) \\ & \text{if } T_{tran} < T_{comp} \end{cases} \tag{6.2}$$

6.2 Simulation Results

To compare the replication-based system with the erasure-coding-based system, we consider two situations: 1) same fault tolerance level and 2) same storage space. In both situations, we always use Hadoop's default replication factor, 3, i.e., $r = 2$, for the replication-based system. Additionally, the block size is set at 64MB by default and $n * 20$GB data will be randomly distributed in FS, that is, about $k = 20GB/64MB = 320$ blocks per node. Based on the performance comparison of different erasure coding libraries in [23], we employ $Jerasure$ erasure coding in our system. Moreover, we simulate clusters of different sizes ranging from 14 nodes to 290 nodes, and every cluster is divided into FS, ES and WS. Basically, 2 nodes are put into WS as backups, and one third of the remaining nodes are treated as FS nodes. Hence, we have $\frac{14-2}{3} = 4$ FS nodes in the smallest cluster while $\frac{290-2}{3} = 96$ FS nodes in the largest cluster, i.e., n ranges from 4 nodes to 96 nodes. As described in Chapter 4, the number of nodes in ES depends on the redundancy mechanism. If replication approach is used, we have $r * n = 2 * n$ nodes in ES, that is, all the remaining nodes of a cluster. While if erasure coding based approach is used, $e * \frac{n}{d}$ nodes is contained in ES.

- **Same Fault Tolerance Level**

  In order to compute the total energy consumption spent in erasure-coding-based system, we still need to know the amount of time spent for decoding an erasure coding set, i.e., T_{comp}. According to the erasure coding algorithm mechanism, when the fragment size is fixed, the decoding time of a set depends on its size and encoding rate, i.e., d and $\frac{d}{d+e}$. When we consider the same fault tolerance level, i.e., $e = r = 2$. Table 6.1 presents the corresponding decoding time on a node as the set size d changes[1].

[1] If the computing capability of a node that executes decoding tasks is fixed, a quadratic model can be built to estimate the decoding time of an erasure coding set for given d and e.

Table 6.1: Time spent by Jerasure's erasure coding ($e = 2$)

blocks per set ($d + e$)	encoding rate ($\frac{d}{d+e}$)	Decoding time (s)
5	$\frac{3}{5}$	0.514
6	$\frac{4}{6}$	0.756
7	$\frac{5}{7}$	0.874
8	$\frac{6}{8}$	1.086
10	$\frac{8}{10}$	1.754
12	$\frac{10}{12}$	2.889
14	$\frac{12}{14}$	3.98
18	$\frac{16}{18}$	6.442
22	$\frac{20}{22}$	10.598
26	$\frac{24}{26}$	16.363

In order to calculate E_{SR} and E_{EC}, according to Equation (6.1) and (6.2), the number of machines in ES to be activated, i.e., A_{SR} and A_{EC}, should be derived. Basically, given a cluster, we simulate a random node failure 10 times and use the average value of these experiments as an estimation of A_{SR} and A_{EC}. Table 6.2 shows the corresponding A_{SR} and A_{EC} when handling a node failure in FS. The resultant energy consumptions are also presented in Table 6.2. While n stands for the number of nodes in FS, $n(ES)_{EC}$ gives the number of nodes in ES when erasure coding mechanism is applied[2]. $n(ES)_{EC} = e * n/d = 2 * n/d$. As Table 6.2 shows, a much fewer number of ES nodes need to be activated when we adopt the erasure-coding-based ES. As indicated by $\frac{E_{SR}}{E_{EC}}$, the corresponding energy consumption is also smaller with 1.87 as the average value. Figure 6.1 shows the energy saving advantages of erasure-coding-based system as cluster size increases[3]. Besides, as another major benefit of erasure coding, storage space can be saved while maintaining the same level of fault

[2]While not given explicitly in the table, the number of nodes in FS is always $r * n = 2 * n$ when replication method is used.

[3]Note that, in Figures 6.1 - 6.6, given a cluster, we use the lowest energy consumption E_{EC} (which is achieved with an optimal setting of d) of the erasure-coding-based system. This is because based on the

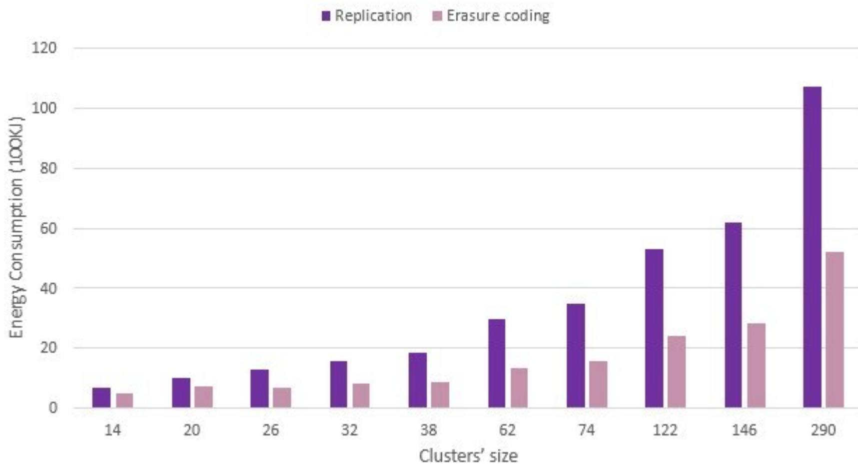


Figure 6.1: Comparison on energy consumption of replication-based system vs erasure-coding-based system (same fault tolerance level)

tolerance. Specifically, if we store the same amount of data in FS, i.e., the same number of unique data blocks in the cluster, the total number of nodes needed for erasure-coding-based ES is much less than that for replication-based ES.

After comparing the two algorithms without the recovery aware data placement strategy enabled, we carry out the simulations by enabling the recovery aware data placement strategy in the algorithms. Table 6.3 presents the results with the recovery aware data placement strategy plugged in. As we expected, Table 6.2 and Table 6.3 show that a fewer number of machines are activated when recovering a single node failure in a cluster when we adopt the recovery aware data placement strategy. In general, the erasure-coding-based system still consumes less energy in failure recovery with 1.52 as the average value of $\frac{E_{SR}}{E_{EC}}$. Similar to Figure 6.1, Figure 6.2 characterizes the trend of energy saving as cluster size increases. In addition, Figure 6.3 compares the energy consumed during a node failure recovery in clusters of different sizes with-/without recovery aware data placement enabled for replication-based systems while

energy model we presented in Chapter 5 and an estimation of decoding time for erasure coding sets (see Table 6.1), the optimal d can be derived easily for a cluster of a certain size.

Figure 6.4 compares that for erasure-coding-based systems. With recovery aware data placement strategy, a fewer number of ES machines are required to be activated to recover a node failure. In replication-based systems, based on Equation (6.1), we know that E_{SR} decreases as A_{SR} decreases. Therefore, in Figure 6.3, energy consumed in a replication-based system with the recovery-aware data placement is always less than the system without the recovery-aware data placement. However, in erasure-coding-based system, A_{EC} not only decides the energy consumed in ES, but also determines a part of energy consumed in FS. Specifically, the system takes $\frac{64*K}{A_{EC}*b}$ seconds[4] to transfer encoded data blocks from A_{EC} ES nodes to $n-1$ FS nodes. As a result, the energy consumption in an erasure-coding-based system is no longer a monotonically increasing function of A_{EC}, as indicated by Equation (6.3).

$$\frac{dE_{EC}}{dA_{EC}} = 24650 - 128*(n-1)*\frac{k}{A_{EC}^2} \tag{6.3}$$

$\frac{A_{EC}^2}{n-1} < \frac{128*k}{24650}$ if $\frac{dE_{EC}}{dA_{EC}} < 0$. That is, when A_{EC} is already small such that $\frac{A_{EC}^2}{n-1} < \frac{128*k}{24650}$, further reducing A_{EC} will lead to an increase in the total energy consumption during the failure recovery. That explains why we observe small increases in energy consumption in the 26 nodes and 30 nodes erasure-coding-based system when data placement strategy is enabled. Similarly, when we have a large FS such that $\frac{A_{EC}^2}{n-1} < \frac{128*k}{24650}$. Energy consumption can also increase as A_{EC} decreases. Consequently, we can conclude that while minimizing the number of nodes to be turned on can always save energy in replication-based system, it is not necessary the case for erasure-coding-based system.

[4] This is based on the analysis in Chapter 5.1, $min(A_{EC}, n-1) = A_{EC}$, because when $d > e = 2$, A_{EC} is smaller than $n-1$.

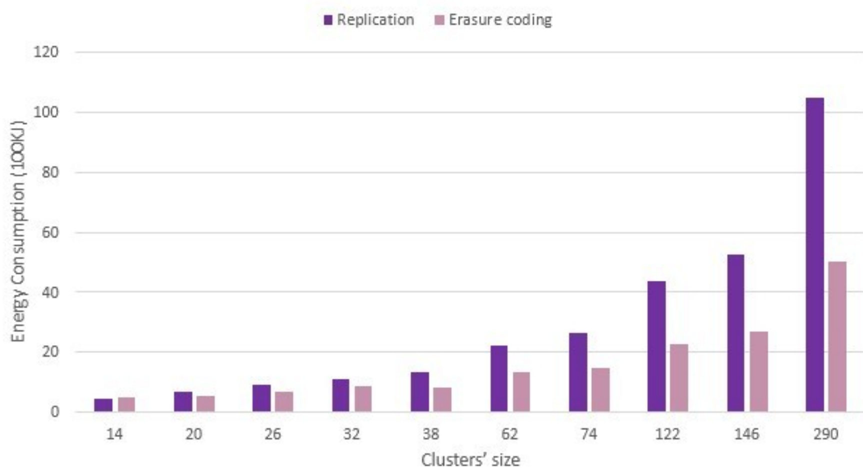


Figure 6.2: Comparison on energy consumption of data placed replication-based systems vs data placed erasure-coding-based systems (same fault tolerance level)

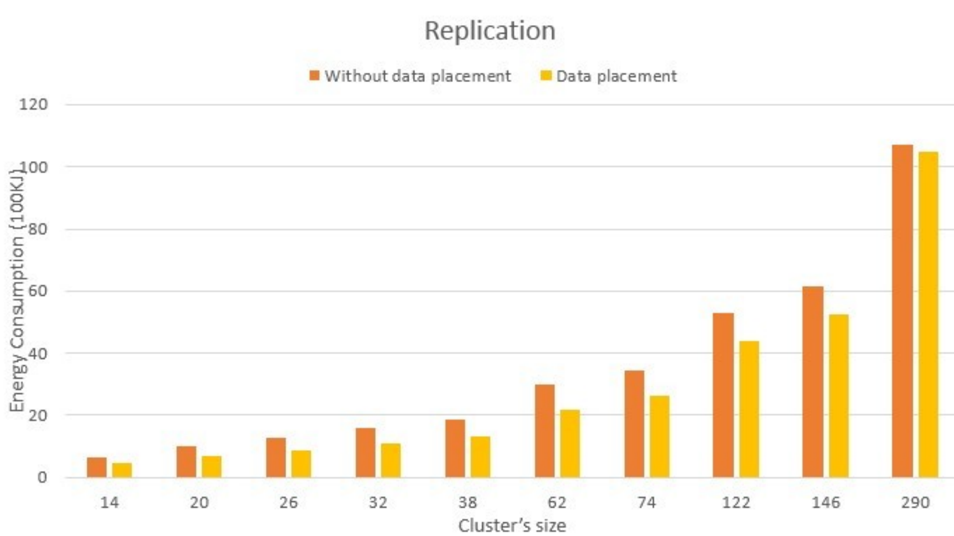


Figure 6.3: Comparison on energy consumption of replication-based systems with/without recovery aware data placement enabled (same fault tolerance level)

- **Same Storage Space**

  Dealing with the same storage space situation, $e = r * d$; Since $r = 2$, we have $e = 2 * d$. In this case, the size of ES, under the two approaches, are the same, i.e., $2 * n$. Table 6.4 shows the time in decoding a set with $e = 2 * d$ as cluster size changes.

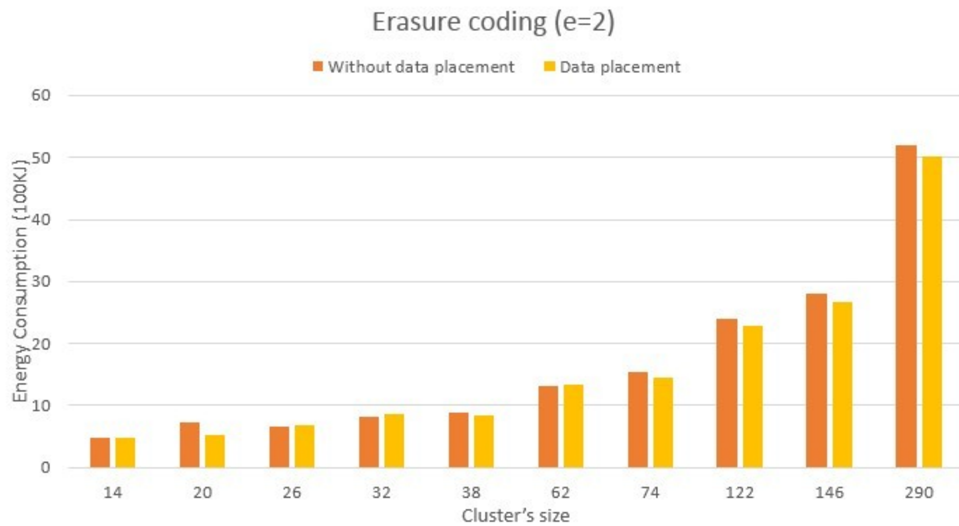


Figure 6.4: Comparison on energy consumption of erasure-coding-based systems with/without recovery aware data placement enabled (same fault tolerance level)

Table 6.4: Time spent by Jerasure's erasure coding($e = 2 * d$)

blocks per set $(d + e)$	encoding rate $(\frac{d}{d+e})$	Decoding time (s)
9	$\frac{3}{9}$	1.532
12	$\frac{4}{12}$	2.266
15	$\frac{5}{15}$	3.411
18	$\frac{6}{18}$	8.108
24	$\frac{8}{24}$	17.618
30	$\frac{10}{30}$	28.474
36	$\frac{12}{36}$	42.401
45	$\frac{15}{45}$	63.984
48	$\frac{16}{48}$	72.404

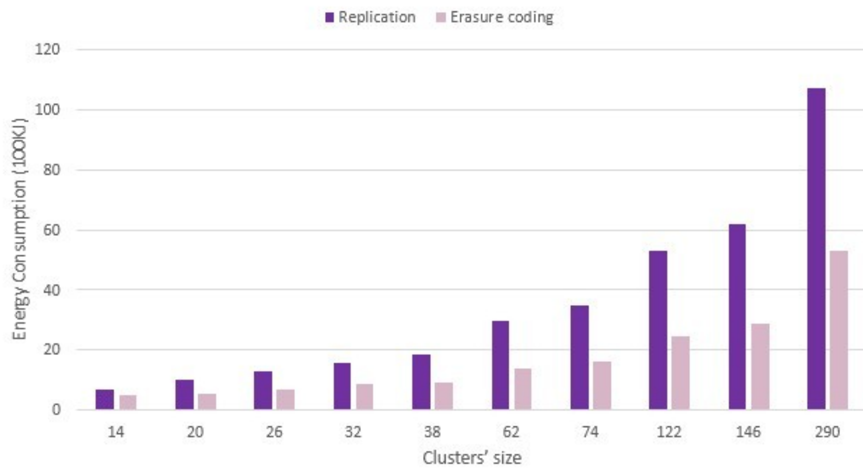


Figure 6.5: Comparison on energy consumption of replication-based system vs erasure-coding-based system (same storage space)

Similar to the case of the same fault tolerance level, we need to carry out experiments to get A_{SR} and A_{EC} to derive E_{SR} and E_{EC}. Table 6.5 reports experimental results. From Table 6.5, we can infer that although the erasure-coding-based approach always outperforms that of replication-based approach in the number of nodes required to be turned on, it does not always consume less energy in the failure recovery. The main reason is that if we choose a larger erasure coding set size, d, decoding cost quickly increases. Nevertheless, most cases presented in Table 6.5 still give the evidence that erasure-coding-based approach is a better choice the the replication-based method as long as we avoid setting d to be too large. For this group of experiments, the average value of $\frac{E_{SR}}{E_{EC}}$ is 1.78. Figure 6.5 displays the relationship between the energy saving and the cluster size. It again shows that the erasure-coding-based system works even better as the cluster size increases.

We also simulate the two algorithms with the recovery aware data placement. Table 6.6 displays the results, where we achieve 1.44 as the mean value of $\frac{E_{SR}}{E_{EC}}$. Moreover, Figure 6.7 compares the energy consumed during a node failure recovery in clusters

Figure 6.6: Comparison on energy consumption of data placed replication-based systems vs data placed erasure-coding-based systems (same storage space)

of different sizes with/without recovery aware data placement enabled for erasure-coding-based systems while Figure [?] describes the comparison for replication-based system[5] In general, less energy is consumed when we adapt the recovery aware data placement. But special attention should be paid to erasure-coding-based system. As we discussed in the same fault tolerance level scenario, E_{EC} is not a monotonically increasing function of A_{EC}. When we have a large FS, energy consumption can increase as A_{EC} decreases. Therefore, we observe a higher energy consumption of the cluster with 96 FS nodes when we plug in recovery aware data placement strategy with d = 12 or 16.

[5]This is because replication-based systems use $r = 2$ in both scenarios, i.e., same fault tolerance level and same storage space as the baseline.

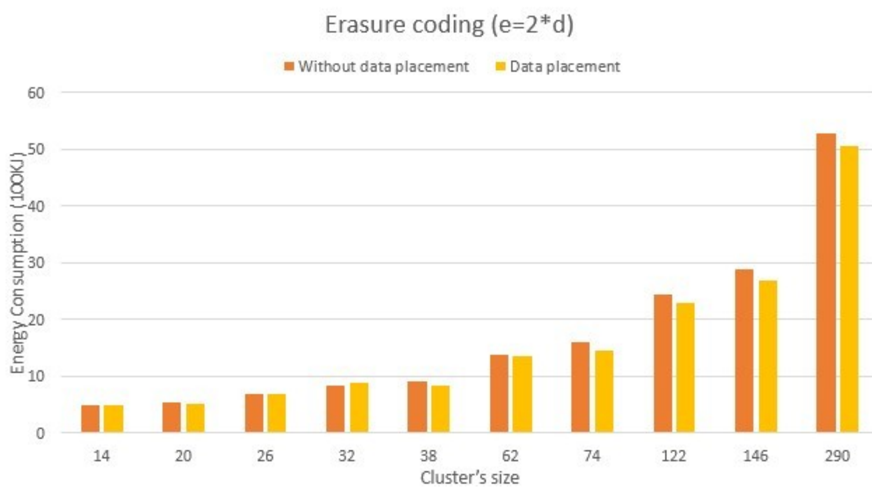


Figure 6.7: Comparison on energy consumption of data placed replication-based systems vs data placed erasure-coding-based systems (same storage space)

Table 6.2: Simulation results from recovering a node failure in clusters of different sizes(same fault tolerance level)

n	A_{SR}	E_{SR}	d	$n(ES)_{EC}$	A_{EC}	E_{EC}	$\frac{E_{SR}}{E_{EC}}$
4	7	654060	4	2	1	470197.16	1.39
6	10.8	989498	3	4	2	517999.5	1.91
			6	2	1	722490.5	1.37
8	13.92	1280321.2	4	4	3	664642.2	1.93
			8	2	1	977205.06	1.31
10	17.18	1580329.9	5	4	3	819964.25	1.93
			10	2	1	1235389.6	1.28
12	20.12	1859343.4	4	6	5	880932.5	2.11
			6	4	3	975993.25	1.91
			12	2	1	1493576.6	1.24
20	31.82	2971460.2	4	10	9	1320795	2.25
			5	8	7	1338073.1	2.22
			10	4	3	1608085.4	1.85
			20	2	1	2546802.5	1.17
24	36.56	3454691.8	4	12	11	1541719.1	2.24
			6	8	6.96	1576409.2	2.19
			8	6	5	1668425.5	2.07
			12	4	3	1926406.5	1.79
			24	2	1	3095867.8	1.12
40	54.3	5307573	4	20	18.76	2422317.8	2.19
			5	16	14.96	2392314.5	2.22
			8	10	9	2447027.2	2.17
			10	8	7	2540722.2	2.09
			20	4	3	3226379.8	1.65
48	62.22	6171684.5	4	24	22.6	2861908	2.16
			6	16	14.94	2801881	2.2
			8	12	10.98	2839133	2.17
			12	8	7	3026123.5	2.04
			16	6	5	3274527	1.88
			24	4	3	3905724	1.58
96	99.48	1.07E+07	3	64	57.32	5725761.5	1.87
			4	48	44.04	5462998	1.96
			6	32	29.98	5244082.5	2.04
			8	24	22.68	5196551.5	2.06
			12	16	14.96	5287680	2.02
			16	12	11	5479673.5	1.95
			24	8	7	6040363	1.77

Table 6.3: Simulation results from recovering a node failure in clusters of different sizes with recovery aware data placement strategy enabled (same fault tolerance level)

n	A_{SR}	E_{SR}	d	$n(ES)_{EC}$	A_{EC}	E_{EC}	$\frac{E_{SR}}{E_{EC}}$
4	4	457230	4	2	1	470197.16	0.97
6	6	674570	3	4	2	517999.5	1.3
			6	1	2	722490.5	0.93
8	8	891910	4	4	2	687778.8	1.3
			8	2	1	977205.06	0.91
10	10	1109250	5	4	2	856754.25	1.29
			10	2	1	1235389.6	0.9
12	12	1326590	4	6	3	891707.2	1.49
			6	4	2	1026436.6	1.29
			12	2	1	1493576.6	0.89
20	20	2195950	4	10	5	1336797.9	1.64
			5	8	4	1347506	1.63
			10	4	2	1713142	1.28
			20	2	1	2546802.5	0.86
24	24	2630630	3	16	8	1456987.1	1.81
			4	12	6	1489838.9	1.77
			6	8	4	1603608.9	1.64
			8	6	3	1744736.2	1.51
			12	4	2	2058769.8	1.28
			24	2	1	3095867.8	0.85
40	40	4369350	4	20	10	2280976.2	1.92
			5	16	8	2313649.5	1.89
			8	10	5	2490422	1.75
			10	8	4	2637926.5	1.66
			20	4	2	3467969.8	1.26
48	48	5238710	4	24	12	2675862.2	1.96
			6	16	8	2742593.2	1.91
			8	12	5	2901420.2	1.81
			12	8	4	3158436.2	1.66
			16	6	3	3481909.5	1.5
			24	4	2	4201927.5	1.25
96	96	1.05E+07	3	64	32	5155337.5	2.03
			4	48	24	5042789	2.07
			6	32	16	5012882.5	2.09
			8	24	12	5085986.5	2.06
			12	16	8	5342409	1.96
			16	12	6	5651211.5	1.85

Table 6.5: Simulation results from recovering a node failure in clusters of different sizes (same storage space)

n	A_{SR}	E_{SR}	d	A_{EC}	E_{EC}	$\frac{E_{SR}}{E_{EC}}$
4	7	654060	4	1	480178.25	1.36
6	10.8	989498	3	5	537381	1.84
			6	1	787390.4	1.26
8	13.92	1280321.2	4	5.02	686381.3	1.87
			8	1	1232134.4	1.04
10	17.18	1580329.9	5	5.06	838552.06	1.88
			10	1	1716667.2	0.92
12	20.12	1859343.4	3	9.78	919320.94	2.02
			4	7.62	925358.8	2.01
			6	5.12	1033580.4	1.8
			12	1	2290669	0.81
20	31.82	2971460.2	4	11.78	1380587.8	2.15
			5	9.98	1397944	2.13
			10	5.2	2042058.8	1.46
24	36.56	3454691.8	3	17.14	1627646.1	2.12
			4	13.74	1604276.4	2.15
			6	9.82	1680234.2	2.06
			8	7.66	1933818.4	1.79
			12	5.02	2658947.2	1.3
40	54.3	5307573	4	20.08	2463044.2	2.15
			5	16.98	2452567.2	2.16
			8	11.82	2749770.5	1.93
			10	9.8	3050471.2	1.74
48	62.22	6171684.5	3	28.56	2957605.2	2.09
			4	23.06	2886179.8	2.14
			6	17	2920256.8	2.11
			8	13.6	3150677.2	1.96
			12	9.78	3849618.2	1.6
			16	7.54	4741031	1.3
96	99.48	1.07E+07	3	44.96	5453034.5	1.96
			4	36.5	5315094.5	2.01
			6	27.2	5292959	2.02
			8	21.72	5492179	1.95
			12	16.1	6178573.5	1.73
			16	12	7072811.5	1.51

Table 6.6: Simulation results from recovering a node failure in clusters of different sizes with recovery aware data placement strategy enabled (same storage space)

n	A_{SR}	E_{SR}	d	A_{EC}	E_{EC}	$\frac{E_{SR}}{E_{EC}}$
4	4	457230	4	1	480178.25	0.95
6	6	674570	3	2	524871	1.29
			6	1	787390.4	0.86
8	8	891910	4	2	698182.75	1.28
			8	1	1232134.4	0.72
10	10	1109250	5	2	874589.3	1.27
			10	1	1716667.2	0.65
12	12	1326590	3	4	843414.44	1.57
			4	3	902533.9	1.47
			6	2	1093952.4	1.21
			12	1	2290669	0.58
20	20	2195950	4	10	1348470.1	1.63
			5	4	1367117	1.61
			10	2	2202637.2	1
24	24	2630630	3	8	1465141.4	1.8
			4	6	1501934	1.75
			6	4	1676356.4	1.57
			8	3	2009989.1	1.31
			12	2	2867879	0.92
40	40	4369350	4	10	2294762.8	1.9
			5	8	2336812.5	1.87
			8	5	2765998.2	1.58
			10	4	3143857.2	1.39
48	48	5238710	4	12	2690494.2	1.95
			6	8	2825804.5	1.85
			8	5	3182158.5	1.65
			12	4	3991579	1.31
			16	3	5015505.5	1.04
96	96	1.05E+07	3	32	5168622.5	2.02
			4	24	5062494.5	2.07
			6	16	5117020.5	2.04
			8	12	5397695	1.94
			12	8	6223619	1.68
			16	6	7249178.5	1.44

Chapter 7

Conclusion

In this thesis, we investigate an energy efficient failure recovery problem in a storage cluster which adopts both a power saving technique and a redundancy mechanism and an erasure coding technique. Specifically, with the purpose of energy saving, only one copy of the original data blocks are stored in Fundamental Set (FS) and are kept online. However, data could be corrupted or node could fail in FS. Redundant information in Extended Set (ES) is used to restore the lost data. To study energy-efficient failure recovery, we consider two different data redundancy mechanisms, i.e., replication and erasure coding. We first develop greedy recovery algorithms for the two systems and then a recovery aware data placement policy to further improve the failure recovery efficiency. For this study, we build energy models and use data collected from our testbed cluster to analyze and estimate the energy cost in recovering a node failure. Simulation results show that, in general, erasure-coding-based system saves about 40% of the energy in a failure recovery when compared with replication-based system. Besides, we also observe that the recovery aware data placement strategy always benefits replication-based systems and also gains energy saving for medium-sized erasure-coding-based systems.

Chapter 8

Future Work

We have simulated and analyzed the energy consumption under different scenarios using data profiled from our testbed cluster. In the future, we plan to validate our simulation results by deploying the failure recovery algorithms in a publicly accessible medium size cluster, i.e., Green Server Farm at University of Illinois at Urbana-Champaign. In this thesis, we have considered a single node failure. We will study the energy efficient multi-node failure recovery problem in the future.

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