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Application and Storage-Aware Data Placement and Job Scheduling for Hadoop Clusters

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Corresponding Author:	Tao Li Hunan University CHINA
Corresponding Author Secondary Information:	
Corresponding Author's Institution:	Hunan University
Corresponding Author's Secondary Institution:	
First Author:	Tao Li
First Author Secondary Information:	
Order of Authors:	Tao Li
	Shuibing He
	Ping Chen
	Siling Yang
	Yanlong Yin
	Cheng Xu
Order of Authors Secondary Information:	
Abstract:	As one of the most popular frameworks for large-scale analytics processing, Hadoop is facing two challenges: both applications and storage devices become heterogeneous. However, existing data placement and job scheduling schemes pay little attention to such heterogeneity of either application I/O requirements or I/O device capability, thus can greatly degrade system efficiencies. In this paper, we propose ASPS, an Application and Storage-aware data Placement and job Scheduling approach for Hadoop clusters. The idea is to place application data and schedule application tasks considering both application I/O requirements and storage device characteristics. Specifically, ASPS first introduces novel metrics to quantify I/O requirements of applications. Then, based on the quantification, ASPS places data of different applications to the preferred storage devices. Finally, ASPS tries to launch jobs with high I/O requirements on the nodes with the same type of faster devices to improve system efficiency. We have implemented ASPS in Hadoop framework. Experimental results show that ASPS can reduce the completion time of a single application by up to 36\% and the average completion time of six concurrent applications by 27\%, compared to existing data placement policies and job scheduling approaches.
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Tao Li
College of Computer Science and Electronic Engineering,
Hunan University, Changsha, China
litao1310@hnu.edu.cn

Shuibing He[†],[*] Ping Chen[‡] and Siling Yang[§]
College of Computer Science and Technology,
Zhejiang University, Hangzhou, China
[†] *heshuibing@zju.edu.cn*
[‡] *zjuchenping@zju.edu.cn*
[§] *slingzjunet@zju.edu.cn*

Yanlong Yin
Intelligent Computing System Research Center,
Institute of Artificial Intelligence, Zhejiang Lab,
Hangzhou, China
yyin@zhejianglab.com

Cheng Xu
College of Computer Science and Electronic Engineering,
Hunan University, Changsha, China
cheng_xu@yeah.net

As one of the most popular frameworks for large-scale analytics processing, Hadoop is facing two challenges: both applications and storage devices become heterogeneous. However, existing data placement and job scheduling schemes pay little attention to such heterogeneity of either application I/O requirements or I/O device capability, thus can greatly degrade system efficiencies. In this paper, we propose ASPS, an Application and Storage-aware data Placement and job Scheduling approach for Hadoop clusters. The idea is to place application data and schedule application tasks considering both application I/O requirements and storage device characteristics. Specifically, ASPS first introduces novel metrics to quantify I/O requirements of applications. Then, based on the quantification, ASPS places data of different applications to the preferred storage devices. Finally, ASPS tries to launch jobs with high I/O requirements on the nodes with the same type of faster devices to improve system efficiency. We have implemented ASPS in Hadoop framework. Experimental results show that ASPS can reduce the completion time of a single application by up to 36% and the average completion time of six concurrent applications by 27%, compared to existing data placement policies and job

[*][†]Corresponding author.

scheduling approaches.

Keywords: Hadoop; MapReduce; HDFS; Data Placement; Job Scheduling; SSDs

1. Introduction

Over the past decade, MapReduce[1] has become one of the most popular parallel frameworks for big data analytics processing. Hadoop[2] is the de facto open-source implementation of MapReduce framework, which consists of Hadoop MapReduce, Hadoop YARN, and Hadoop Distributed File System (HDFS).[3] The Apache community has developed the Hadoop ecosystem to address big-data challenges. Previous study[4] has shown that more than 30% of the companies had already deployed Hadoop. Hadoop has attracted much attention not only in industry but also in academia.

Many large-scale data analytics applications are I/O-intensive. For example, workload analysis from Facebook and Microsoft show that 79% of job execution time is spent on I/O operations.[5] To accommodate the large volumes of data from such applications, Hadoop leverages HDFS to provide efficient data storage services. In addition to Hadoop MapReduce, HDFS is also used in the in-memory data processing framework Spark[6] as well as Hadoop database HBase.[7] However, while HDFS offers promising I/O potential for data-intensive applications, current Hadoop (version 3) is still facing the following challenges due to recent application and storage trends in data centers.

First, Hadoop clusters face multiple heterogeneous applications, which may degrade system performance. For better system resource utilization, Hadoop clusters are commonly shared by multiple applications concurrently.[8–11] Due to their inherent natures, applications may have various I/O requirements to process data (section 2). Unfortunately, current Hadoop cannot intelligently recognize such requirement heterogeneity and still allocates storage resources equally to each application. As a result, some applications may need less bandwidth/capacity than they are assigned while others need more, leading to sub-optimal system performance.

Second, current Hadoop systems host increasingly heterogeneous storage devices, which can also offset system efficiency. To achieve high throughputs with acceptable costs, each node is evolving to heterogeneous storage devices, e.g., hard disk drives (HDDs) and solid-state drives (SSDs).[12,13] However, HDFS is initially designed for homogeneous devices, and thus it places data uniformly across nodes regardless of device characteristics. Consequently, the tasks of a job on the nodes with faster SSDs will often execute quickly and wait for the tasks on the nodes with HDDs. This task skewness will under-utilize the potential of SSDs. While storage heterogeneity could occur in different fashions, in this paper, we focus on the case where each node hosts an HDD and an SSD.

Several previous approaches address the heterogeneity issues by optimizing data placement of Hadoop systems.[4,13–16] Other efforts improve Hadoop throughput by designing new task schedulers.[17–21] Also some approaches tackle the issues with integrated data placement and job scheduling optimization.[22] However, we note that none of them are efficient for Hadoop clusters where applications have heterogeneous I/O requirements and each node hosts heterogeneous storage devices.

In this study, we propose ASPS, an Application and Storage-aware data Placement and job Scheduling approach for Hadoop clusters. Besides data locality in existing approaches, ASPS places application data and schedules application tasks considering application I/O requirements and storage device characteristics. Specifically, ASPS proposes two metrics to quantify the I/O requirements of the map and the reduce task of an application. Then, based on the quantification, ASPS places application data on the proper devices to make full utilization of storage devices. The optimized data placement involves the input data, the intermediate data, and the output data of an application. Finally, ASPS tries to schedule tasks of an application on the same type of nodes to alleviate task skewness within a job execution. It also preferentially schedules applications with higher I/O requirements on the nodes with faster storage devices to enhance system efficiency for multiple jobs. We have implemented ASPS in Hadoop system and demonstrated its advancements through extensive experimental tests on six benchmark applications. Experimental results show that ASPS can significantly reduce application completion time and achieve better cost-effectiveness on storage-heterogeneous Hadoop clusters.

Specifically, this study makes the following contributions:

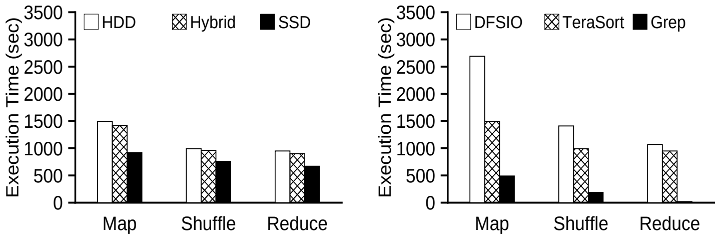
- We present two new metrics, which can be measured with a simple sampling approach, to respectively quantify the I/O requirements of the map task (mapper) and the reduce task (reducer) of a MapReduce application.
- Based on the metrics, we design and develop ASPS, an application and storage-aware data placement and task scheduling approach to enhance Hadoop system performance.
- We implemented ASPS in the Hadoop framework. Experimental results with extensive tests on six benchmark applications validate the effectiveness of ASPS.

The remainder of this paper is organized as follows. In section 2, we describe the background and motivation. In section 3 and section 4, we propose the design and implementation of ASPS respectively. Section 5 presents the evaluation results. Section 6 discusses the related work. Finally, we conclude this paper in section 7.

2. Background and Motivation

2.1. *Hadoop data placement and job scheduling*

Hadoop is an open-source implementation of the MapReduce framework. The first version of Hadoop[1] is composed of Hadoop runtime subsystem that executes the MapReduce applications, and HDFS that provides data storage. The runtime system includes one JobTracker and multiple TaskTrackers. The JobTracker schedules tasks onto the TaskTrackers. The Hadoop 2.0/3.0 version has a new module called



(a) Heterogeneous devices

(b) Heterogeneous applications

Fig. 1. The system performance in heterogeneous environments.

YARN, which separates the role of JobTracker into two parts: ResourceManager and AppMaster. These two parts manage system resources and monitor task execution, respectively. There are multiple nodes in the Hadoop system. A small number of nodes are connected to form a rack. A Hadoop cluster may consist of one or more racks.

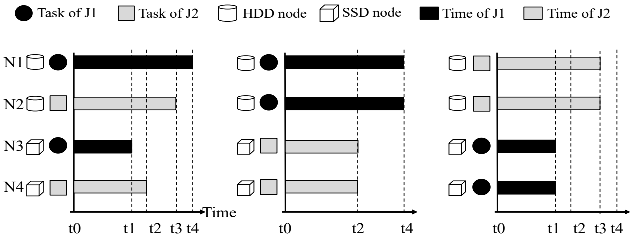
HDFS[3] is composed of one NameNode that manages file metadata and multiple DataNodes that store file data. To provide high throughput, HDFS divides all files into fixed-size blocks (e.g., 64MB) and places them uniformly across various DataNodes. Moreover, to provide resilience against both node and rack failures, HDFS defaults to maintain three replicas for each block and places them on DataNodes in a *network-aware* fashion: one is placed on the local node where the client is running, one on a node in another rack, and one on a different node in the remote rack. Each input data block corresponds to one map task (mapper). When a job begins to run, the scheduler (Capacity Scheduler) uses a network-aware policy to assign each map task on a DataNode where the nearest replica of the required data resides. These network-aware policies can significantly improve data locality and reduce data transfer time on the network.

As described in section 1, the original Hadoop implementation regards all applications and storage devices to be homogeneous. While recent versions of Hadoop have supported heterogeneous storage devices,[23–25] they only provide interfaces for users to choose the desired device types rather than intelligently determining the preferred devices and scheduling the jobs in the system. When various applications and storage devices occur, existing Hadoop systems may lead to sub-optimal system performance.

2.2. *Motivating examples*

To highlight these issues, we measure the Hadoop system performance in two different scenarios: homogeneous applications on heterogeneous devices and heterogeneous applications on homogeneous devices. We use three PUMA benchmark applications,[26] i.e., DFSIO, TeraSort, and Grep, each with 40 GB input data.

Heterogeneous device impact. Figure 1(a) shows the completion times of



(a) Default policy **(b) Storage-aware policy** **(c) Cost-effective policy**

Fig. 2. Job execution under different policies in Hadoop system.

different phases of TeraSort on three storage configurations. The HDD, SSD, and Hybrid configurations refer to 8 HDD DataNodes, 8 SSD DataNodes, and 4 HDD+4 SSD DataNodes, respectively. As shown, for all the three phases, i.e., Map, Shuffle, and Reduce phase, Hybrid configuration slightly outperforms the homogeneous HDD cluster and is much worse than the homogeneous SSD configuration. This shows the potential of SSD DataNodes is substantially under-utilized in storage-heterogeneous environments.

The reason is that heterogeneous devices lead to skewed task execution, which offsets application performance. To illustrate this issue, we use Figure 2(a) as an example to describe job execution on a storage-heterogeneous cluster. There are two jobs, J1 and J2, running on four nodes, N1 to N4. Each job represents an application. For J1, its two input blocks (the nearest replicas) are placed on N1 and N3, which have an HDD and an SSD device respectively. With the default policy, two tasks of J1 are scheduled on N1 and N3. Because an SSD has higher I/O performance than an HDD, N3 finishes its task more quickly than N1. However, J1's completion time is t_4 because a job is not completed until the slowest task complete.[5] This is called the "*all-or-nothing*" property of job execution, which offsets SSD potential though it has superior performance. The case is similar for job execution of J2.

To overcome the above issue, an alternative approach is to place data of a job in the same type of devices and schedule its tasks from the same type of nodes. We refer this policy to *storage-aware* policy. As shown in Figure 2(b), the input blocks of J1 are placed on HDD nodes, namely N1 and N2, and those of J2 are on SSD nodes, namely N3 and N4. During job execution, J1 is scheduled on HDD nodes and J2 on SSD nodes. As a result, the job completion times of J1 and J2 are t_4 and t_2, respectively. Compared to the default policy, the storage-aware policy reduces the job completion time from $t_3 + t_4$ to $t_2 + t_4$.

Heterogeneous application impact. Figure 1(b) shows the completion times of the three heterogeneous applications with the HDD configuration. One can observe that these times in the three phases vary significantly for the three applications. The reason is that applications access the data with different I/O requirements. Usually, each task of an application handles a data block consisting of several records. The number of records, the record size, and the read/write intensity can vary greatly from application to application. This means allocating enhanced resource to different applications results in various performance benefits. For example, the Mapper execution times of TeraSort and Grep are reduced by 1.6X and 1.1X respectively when running them on SSD nodes compared to running them on HDD nodes. Therefore, such storage-aware policy may still be sub-optimal because it ignores application characteristics. We will illustrate this in section 3.1 later.

Summary. The above studies show that both heterogeneous devices and heterogeneous applications can substantially impact Hadoop system efficiency. This motivates us to propose ASPS to tackle these challenges.

3. ASPS Design

ASPS aims to enhance Hadoop with a cooperative data placement and job scheduling approach. In this section, we first introduce the idea of ASPS, and then describe its architecture, followed by the details of each of its key components.

3.1. *Idea of ASPS*

Since applications own different I/O requirements and storage devices provide various I/O capacities, ASPS places application data and schedules their tasks considering both application and device characteristics. ASPS centers on two key designs: (1) it tries to place an application's data on the same type of devices like in the storage-aware policy. Moreover, as applications with high I/O requirements will bring significant performance benefits from fast devices, it prioritizes to place data of such applications on faster devices, i.e., SSDs; (2) it preferentially schedules the tasks of applications with high I/O requirements on the nodes with the same type of faster devices.

Figure 2(c) shows the idea of ASPS, which we call a *cost-effective* policy. In the example, as J1 has higher I/O requirement than J2, the blocks of J1 are placed on SSD nodes (N3 and N4) and those of J2 are on HDD nodes (N1 and N2). Moreover, by scheduling J1 and J2 on the same type of SSD nodes and HDD nodes respectively, the overall job completion time is $t_1 + t_3$, which is smaller than $t_2 + t_4$, namely the time achieved by the storage-aware policy in Figure 2(b).

The proposed approach requires prior knowledge of applications' I/O requirements. Fortunately, periodic jobs make up the majority of cluster workloads, as reported by.[27,28] This provides an opportunity to obtain the I/O requirements of application via I/O sampling techniques.

3.2. *System architecture*

Figure 3 shows the system architecture of ASPS. In this system, we assume that each node in the cluster is equipped with homogeneous CPU and memory resource but with heterogeneous storage devices: an HDD and an SSD. There are concurrent

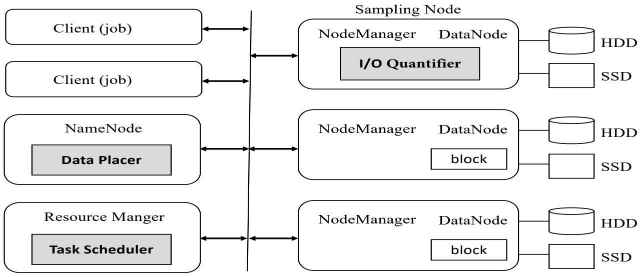


Fig. 3. The system architecture of ASPS.

jobs (applications) submitted to the cluster. To enable the proposed application and storage-aware data placement and job scheduling approach, ASPS includes the following three components.

- **The I/O quantifier.** It uses a simple but effective sampling technique to quantify the I/O requirements of applications. Based on these metrics, ASPS makes optimized data placement and task scheduling.
- **The data placer.** It places application data on the proper devices based on their I/O requirements. The data include the input data, the intermediate data, and the output data of the application in the I/O path of the job execution.
- **The job scheduler.** It makes efficient scheduling for concurrent jobs by considering application I/O requirements and storage device types.

The above components operate as follows. Firstly, the quantifier recognizes the I/O requirements of applications, and then forwards these requirements to the NameNode. Then, when the input data of applications are imported into HDFS, the data placer makes careful data placement on the proper storage devices based on the application's I/O requirements. Finally, when multiple jobs are concurrently submitted to the system, the scheduler allocates the jobs to the proper nodes based on application and device characteristics. This process is repeated until all jobs are completed.

3.3. *I/O requirement quantification*

To enable the proposed data placement and task scheduling approach, we need to quantify the I/O requirements of applications. These requirements are highly application-dependent, thus the measurements change for different applications. Since map tasks and reduce tasks may require various I/O operations (section 2.2), we further quantify the I/O requirements of mappers and reducers, respectively.

Inspired by previous studies that use disk-based sampling technique to learn the features of MapReduce applications,[29] we propose a disk-based sampling approach to measure the I/O requirements of mappers and reducers. We use an in-disk directory as the local HDFS storage and capture the I/O timing information and the input/output data amounts of applications.

For mappers, we use one tailored map task and run it on a dedicated node to process a split that is approximately a block. We measure the split size and the mapper I/O times on different storage devices. Assume the split size is B, the I/O times on an HDD and an SSD device are T_m^h and T_m^s, respectively, then the I/O requirement of the mapper is defined as

$$r_m = \frac{T_m^h - T_m^s}{B} \tag{1}$$

For reducers, they will read input data from the outputs of mappers, which are expected to be materialized in the local file system. Assume the output size of a mapper is D, then the input size of a reducer is $\frac{D \times m}{r}$, where m and r mean the number of mappers and reducers, respectively. We also measure the reducer I/O times on different storage devices. Assume the I/O times on an HDD node and an SSD node are T_r^h and T_r^s, then the I/O requirement of the reducer is

$$r_r = \frac{r \times (T_r^h - T_r^s)}{D \times m} \tag{2}$$

Both r_m and r_r reflect the I/O time reduction brought by per unit of fast storage resource. The larger the values of r_m and r_r, the higher the I/O requirements of the mapper and the reducer.

Note that r_m and r_r are efficient for all mappers and reducers only when they have uniform workloads. For example, all mappers have a uniform number of input and output key-value pairs, and the number of values for each output key is similar. In this case, r_m is relatively stable in terms of different sampling split sizes and mappers, and the mapper completion time is often linearly proportional to the input size.[16] As such, we can quantify the requirements of all mappers with a sampling task and a split. However, this assumption does not always hold true for some non-trivial applications in real-world scenarios. To address this issue, we run the sampling procedure with multiple randomly selected splits and choose the averages as the final metrics of r_m and r_r, respectively.

The quantifier identifies I/O requirements of all applications one by one. Once this process is over, it will store the obtained information into a global requirement table, which is used by the placer and scheduler later. Note that the two metrics only considers limited parameters in characterizing I/O accesses. There are other factors that affect the application's I/O performance. However, such metrics account for the major I/O access features. As shown in the evaluation, they are a reliable indicator to direct data placement and job scheduling.

3.4. *Data placement*

With the proposed metrics in section 3.3, the placer distributes application data on the cluster with the following rules. (1) It tries to place the data of an application

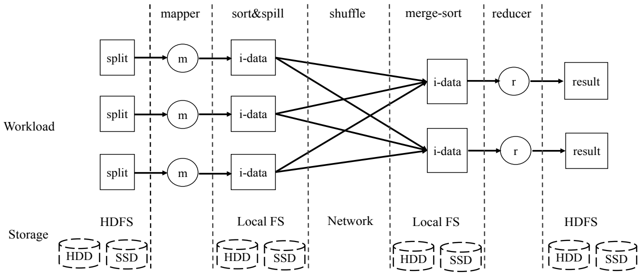


Fig. 4. Typical I/O path in our system.

from the same type of devices as in the storage-aware policy. (2) As applications with high I/O requirements will bring significant performance benefits from fast devices, it tries to place data of such applications on SSD nodes in a high priority. Specifically, if the application has high I/O requirements (A high value of r_m) and the SSDs have enough space, the placer will store two of the replicas of each block on SSDs and one replica on HDDs. Otherwise, the placer will store all the replicas on HDDs. This policy tries to allocate more space for applications with high I/O requirements so that SSDs can be efficiently used.

The default HDFS places three replicas of a block on DataNodes in a network-aware fashion (section 2). Note that the placer does not break this policy: it first uses the network-aware policy to find the physical node that hosts an HDD and an SSD, and then it adopts the above rules to place the replica on the ultimate device, an SSD or an HDD, according to application characteristics. To shorten the write response time of a client, the placer stores the primary replica of the block on SSDs if it is possible.

Besides the input data of map tasks, the placer also optimizes the data placement of the intermediate data. We do this because the intermediate data materialization is an I/O-intensive procedure and it can substantially impact overall job execution.[30, 31] Figure 4 shows the typical I/O path of Hadoop application. We adopt the following rules to optimize the placement of intermediate data on local devices. For map tasks, if the value of r_m is high and the local SSD has enough free space, we store the outputs of the map tasks in the local SSDs. Otherwise, the data will be stored on local HDDs. For reduce tasks, we use similar rules to place their input data except that r_m changes to r_r.

Finally, the placer also optimizes the data placement of the output data of the application. Similar to the rules for the input data of map tasks, we store the output data of reduce tasks in the HDFS file system as following. If the value of r_r is high and SSDs have enough space, we will store two replicas of each block in the output file on SSD nodes and one replica on an HDD node. Otherwise, we will store all the replicas on HDD nodes.

Algorithm 1 Cost-Effective Job Scheduler

```
procedure JOB_SCHEDULING($j$, $R$)
    $m \leftarrow$ number of map tasks of job $j$
    $r \leftarrow$ number of reduce tasks of job $j$
    $\mathcal{J}_w \leftarrow$ waiting job set in current sliding window
    $\mathcal{J}_a \leftarrow$ active job set in current sliding window
    $r_m \leftarrow$ map task I/O requirement of job $j$
    $r_r \leftarrow$ reduce task I/O requirement of job $j$
    $\mathcal{J}_w \leftarrow \mathcal{J}_w + j$

    while $\mathcal{J}_w \neq 0$ do                                  ▷ Thread 0
        pick a job $i$ with the highest $r_m$
        if all its map tasks can be assigned on SSD nodes then
            allocate the resource on SSD nodes to job $i$
        else
            allocate the resource as default policy to job $i$
        end if
        update current available resource $R$
        $\mathcal{J}_w \leftarrow \mathcal{J}_w - i$
        $\mathcal{J}_a \leftarrow \mathcal{J}_a + i$
    end while

    while $\mathcal{J}_a \neq 0$ do                                  ▷ Thread 1
        pick a job $k$ with the highest $r_r$
        if all its reduce tasks can be assigned to SSD nodes then
            allocate the resource on SSD nodes to job $k$
        else
            allocate the resource as default policy to job $k$
        end if
        update current available resource $R$
        $\mathcal{J}_a \leftarrow \mathcal{J}_a - k$
    end while
end procedure
```

3.5. *Job scheduling*

Based on the proposed data placement policy and I/O metrics, the scheduler assigns multiple jobs to the nodes in the cluster as Algorithm 1. The key idea consists of two aspects. First, considering the "*all-or-nothing*" property within a single job execution, the algorithm tries to launch tasks of each job on the nodes with the same types of devices. Second, to achieve the cost-effectiveness of multi-job execution, the algorithm schedules the tasks of application with high I/O requirements on SSD nodes to utilize the potential of SSDs.

To this end, the algorithm leverages two helper threads to schedule the tasks of multiple jobs in the system. One thread is responsible for scheduling map tasks and the other for reduce tasks. The two threads are synchronized by a waiting job set ($\mathcal{J}_w$) in the current sliding time window. Each thread uses its own I/O metric, i.e., r_m or r_r, to determine if all tasks of a job in a wave can get the same I/O resource. If yes, the corresponding resources, including CPU, memory, and storage device, are allocated to the job, and this job will be scheduled with these resources. Otherwise, the job is scheduled as the default policy as long as the system has available resources for the current wave of job execution. Each thread uses a loop to schedule all tasks in the job set until all jobs are completed.

For a single job, as all of its tasks may be launched onto the nodes with the same type of devices, the task skewness within the job execution will be substantially alleviated. For multiple jobs in the system, as those jobs with high I/O requirements are preferentially executed on the nodes with fast SSDs, the overall system efficiency will be improved as the high-performance SSDs are used in a more efficient fashion.

Note that this algorithm does not break the data locality in traditional network-aware scheduler: it first tries to use the network-aware policy to find the physical node that hosts the required data, then it adopts the above rules to schedule the jobs on the node by accessing the ultimate device, an SSD or an HDD, according to application characteristics. Moreover, the algorithm is not only limited by one-wave task execution, but it also applies to multi-wave workloads, namely large jobs.

4. Implementation

We implemented ASPS under Hadoop version 3.0.3. Figure 5 shows the overview of the system implementation, which includes three phases. In the sampling phase, the map task of each application is profiled on a sampling node to measure application I/O requirements. In the data placement phase, the NameNode guides the data placements of each application on storage devices according to the collected I/O requirements. In the scheduling phase, the scheduler assigns tasks to the proper nodes based on the rating information.

4.1. *Heterogeneous device management*

To manage the heterogeneous storage within a single physical node, we run two DataNodes simultaneously on the same machine. We specify different server addresses and ports in the configuration file to differentiate the DataNodes. Meanwhile, we configure the "*dfs.data.dir*" to an HDD and SSD-mounted directory to access the HDD and SSD devices, respectively. The start-up script of HDFS is also modified to make the DataNodes start with different configuration files. The NodeManager, which manages the task running on its hosting node, is the same as the

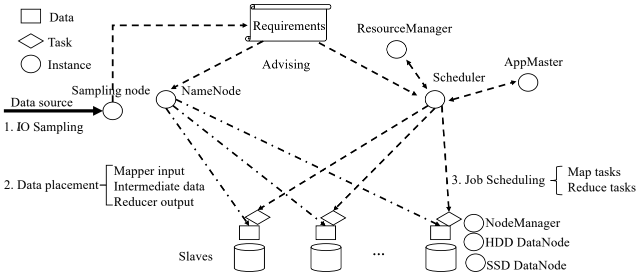


Fig. 5. System Implementation overview of ASPS.

conventional YARN deployment. However, it interacts with both DataNodes.

To enable our proposed schemes, the ResourceManager or Scheduler in YARN needs to know the storage device information in each NodeManager. However, existing computing resources in YARN are abstracted by container, which mainly include CPU and memory resources without storage information. To overcome this issue, we encode the storage information into the port number of the NodeManager, such that the ResourceManager can recognize what the storage device the NodeManager owns according to the port number.

4.2. *I/O metric sampling*

Before importing the input data of applications into HDFS, we use a dedicated machine as a sampling agent to measure their I/O requirements. As we discussed in section 3.3, we use disk-based storage to quantify application I/O features. This can be achieved by specifying the data storage path to an HDD or SSD-based local file system. We tailor the *copyFromLocal* approach to load one or more data blocks into the memory. We run a customized map task to generate the desired metrics, i.e., r_m and r_r. Specifically, we add timing information at the beginning and the ending of the map task execution in MapRunner and record the map output size.

The sampling information is kept in a data structure in NetworkTopology instance. This information will be periodically delivered to the NameNode and the task scheduler via customized RPCs.

4.3. *Data placement*

To place input data blocks on desired devices of DataNodes, we modify the block placement function executed by NameNode. The existing data placer chooses DataNodes in a network-aware fashion by considering the NetworkTopology, where leaf nodes represent data nodes while intermediate nodes denote routers of a rack. To make the data placement policy application- and storage-aware, we hack the NetworkTopology with storage device information. We then intercept the DataNode choosing function and choose the desired DataNode by the IP address and port number. Similar to the default data placement policy, we avoid allocating two replicas of a block on the same physical node.

By default Hadoop stores the intermediate data in the path specified by "*hadoop.tmp.dir*" in the pre-configured *mapred-site.xml* file. However, all applications in the system share the same configuration. To store the intermediate data on the desired type of devices, we modify the implementation of the AppMaster and the ResourceManager. When the AppMaster executes its ServiceInit procedure, we capture the appName and put it into the PRC issued to the ResourceManager. The ResourceManager determines the data store paths for the intermediate data according to the appName and sends this information to the AppMaster. Once the AppMaster receives the feedback from the ResourceManager, it knows the application-specific path to store the intermediate data for map task outputs and reduce task inputs.

For the outputs of reduce tasks, we use a similar method as in the input placement of map tasks to distribute their data on the specific DataNodes in the HDFS file system.

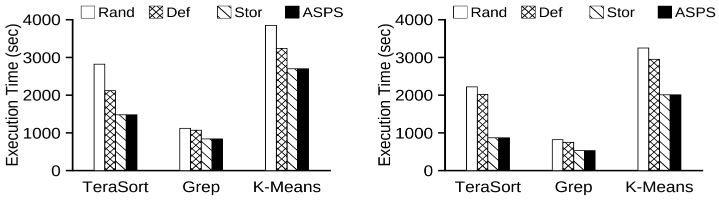
4.4. *Task scheduling*

A computing resource in YARN is denoted by a container. The ResourceManager manages all resources in the cluster. When a job is submitted to the system, the scheduler in ResourceManager will allocate resources to the AppMaster, which is in charge of executing the tasks of the job. The AppMaster asks the ResourceManager for desired resources, including resource priorities, desired nodes, the number of containers, and resource types. The default scheduler in YARN is Capacity Scheduler, which tries to fulfill the container requests from the AppMaster following a node-local, rack-remote, and rack-remote order. However, it does not consider the storage heterogeneity information.

To schedule tasks cost-effectively, we modify the Capacity Scheduler to meet the I/O requirement of a particular application with a high priority. We add a control switch in the container selection strategy to choose the DataNode with a specific storage device. In the system, each NodeManager periodically reports its resource information to ResourceManager via heartbeats. ResourceManager acknowledges back a heartbeat, including container releasing information. Since the container has application and task information, the ResourceManager learns if it can get the preferred resource according to the port numbers of the NodeManagers.

5. Evaluation

In this section, we first evaluate ASPS in a storage-heterogeneous cluster for a single application. Then, we further prove the efficiency of ASPS in the storage-heterogeneous cluster for multiple heterogeneous applications.



(a) Application Completion Time (b) Map Task Completion Time

Fig. 6. Application performance when mapper input placement and scheduling optimization are enabled in ASPS.

5.1. *Experimental setup*

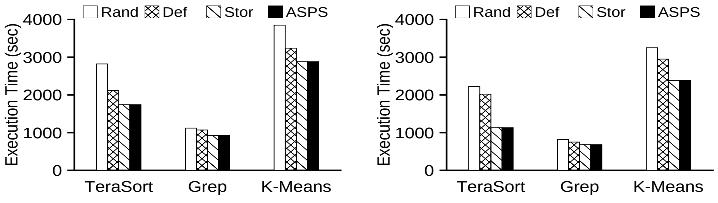
We conduct experiments on a 17-node Linux cluster, including one head node and 16 computing nodes. The head is equipped with dual 2.7 GHz Opteron quad-core processors, 8GB memory, and a RAID5 array. Each computing node has two Opteron quad-core processors, 8GB memory, a 250GB HDD, and a 100GB SSD. Gigabit Ethernet connects all nodes. We use the head node as Master and the 16 computing nodes as Slaves. The operating system on each node is Ubuntu 13.04. The Hadoop version is 3.0.3.

We compare ASPS with three other schemes: Def is the default policy in Hadoop, which only considers network characteristics (or data locality) but ignores storage and application information; Stor accounts for both storage and network but is unaware of application characteristics; Rand is totally random and oblivious of all information. Both Def and Stor are discussed in section 3. In contrast, ASPS considers network, storage, and application factors. By default, the replication factor in HDFS is three and the block size is 64MB. The input size is 128GB for each application and the number of reducers is 4.

5.2. *Evaluation with a single application*

In this set of experiments, we use three MapReduce applications, i.e., TeraSort, Grep, and K-Means from the PUMA benchmark.[26] To evaluate ASPS for a single application, we conduct the experiments by running each benchmark, respectively.

Mapper input placement and scheduling optimization. Figure 6 shows the application performance when only the mapper input data placement and map task scheduling are enabled in ASPS. As shown in Figure 6(a), Rand has the longest completion times because it does not consider network, storage, and application characteristics. Compared to Rand and Def, ASPS reduces the job completion times of TeraSort, Grep, and K-Means by 47% and 31%, 25% and 21%, and 19% and 16%, respectively. The reason for these improvements is that ASPS places application data on SSDs and launches all mappers from the nodes with the same type of devices, such that the data retrieval of each mapper can be accelerated and the task skewness across mappers can be alleviated. In contrast, Rand and Def fully



(a) Application Completion Time (b) Map Task Completion Time

Fig. 7. Application performance when mapper output placement optimization is enabled in ASPS.

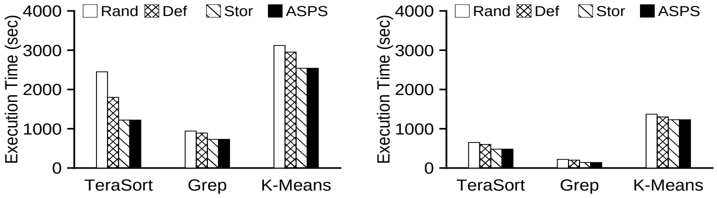
ignore storage device characteristics. We also observe that ASPS is comparable to Stor since there is only one application in the system thus ASPS defaults to Stor. Figure 6(b) shows the map phase times of the three applications. Similar to Figure 6(a), we can find ASPS outperforms Rand and Def in reducing the map task completion times of the three applications.

Another observation from Figure 6 is that ASPS achieves larger performance improvements for Grep and TeraSort than for K-Means. By analyzing the I/O times and overall completion times of the three applications, we find that Grep and TeraSort are I/O intensive workloads while K-Means is a CPU intensive workload. Since ASPS focuses on data storage optimization in the I/O path, it accordingly brings more performance benefits for I/O intensive workloads Grep and TeraSort.

Mapper output placement optimization. Figure 7(a) compares application completion times when only mapper output data placement optimization is enabled in ASPS. This means that ASPS will store the output data of map tasks on local SSDs. One can find that ASPS improves job completion times by 10% to 17% against Rand and Def. This shows placing the intermediate data on fast devices can efficiently improve the overall application performance. Figure 7(b) shows the corresponding map task completion times. ASPS contributes 15% to 26% performance improvements, which are larger than those improvements of the overall application completion times. Similarly, ASPS has comparable performance with Stor because it defaults to Stor in the single-application case.

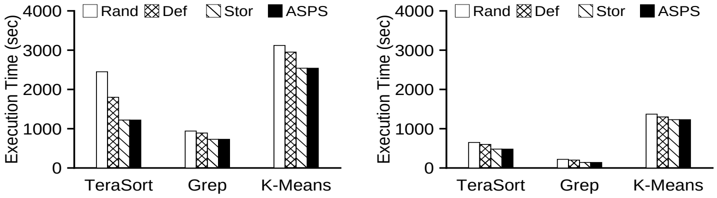
Reducer input placement optimization. Figure 8 shows the application execution times when only the reducer input data placement optimization is enabled in ASPS. This means that ASPS will store the input data of reduce tasks on SSDs if the intermediate data are materialized in the local file system. To show the impacts of reduce task data placement on application performance, we set the number of reducers to 16. ASPS improves job completion time by 7% to 13% compared to Rand and Def. The reason is that both Rand and Def randomly store the materialized input data of reduce tasks in the local file system on HDDs while ASPS stores them on fast SSDs. This can greatly speed up the I/O materialization procedure.

Reducer output placement and scheduling optimization. Figure 9 plots the application completion times when only the reducer output placement and



(a) Application Completion Time (b) Reducer Completion Time

Fig. 8. Application performance when reducer input placement optimization is enabled in ASPS.



(a) Application Completion Time (b) Reducer Completion Time

Fig. 9. Application performance when reducer output placement and scheduling optimizations are enabled in ASPS.

scheduling optimization are enabled. In this case, ASPS tries to place application data on SSDs and to schedule all reducers on the nodes with the same type of devices. We set the number of reducers to 16. ASPS improves the job completion time of TeraSort by 14% and 27% compared to Rand and Def on the heterogeneous cluster, respectively. The reason is that both Rand and Def place data and schedule tasks in a storage-unaware fashion, thus some reducers are allocated to nodes with HDDs and others are allocated to nodes with SSDs, leading to severe task skewness in the reducer execution. In contrast, ASPS attempts to launch reducers on the nodes with the same type of fast SSDs, which not only speeds up write accesses but also alleviates task skewness across reducers, leading to enhanced system performance.

Comprehensive optimization. Figure 10 plots the application performance when all the optimizations in ASPS are enabled. While it only shows the results of TeraSort with four reducers (4R) and 16 reducers (16R), the results of other applications bring a similar conclusion. Compared to Def, we can see that ASPS improves the overall performance by 36% and 32%, respectively, for four reducers and 16 reducers. This indicates that ASPS can efficiently reduce application completion time when combining all optimizations compared to the case where only one optimization is used. However, the overall improvement cannot be the sum of that of each optimization. This is because some of the execution phases run concurrently. For example, the reduce phase overlaps with the map phase, which will

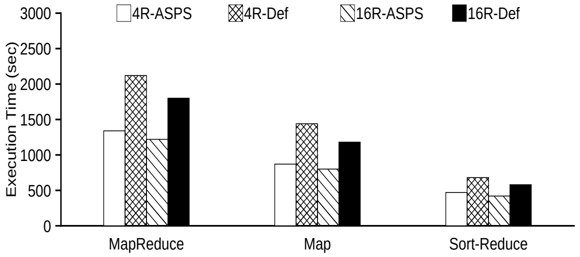
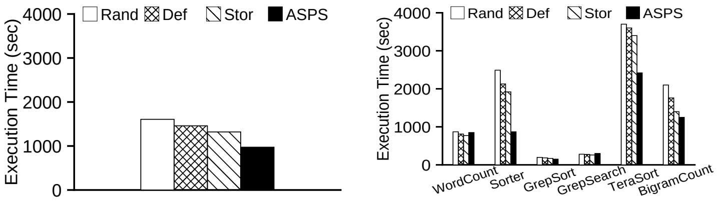


Fig. 10. TeraSort performance when all optimizations are enabled in ASPS.



(a) Average Completion Time

(b) Individual Completion Time

Fig. 11. Completion Times of Applications.

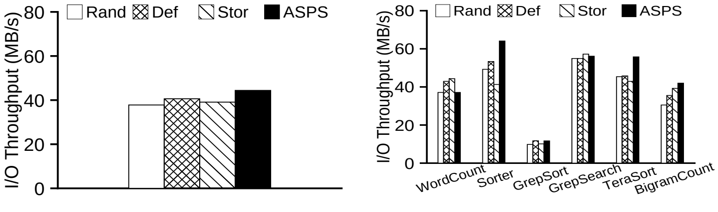
compromise the performance improvement of each phase.

5.3. *Evaluation with multiple applications*

In this set of experiments, we evaluate ASPS on the storage-heterogeneous cluster with six concurrent applications, i.e, WordCount, GrepSort, GrepSearch, TeraSort, Sorter, and BigramCount. The former four applications are from the PUMA benchmark.[26] The BigramCount is from Cloud[9] MapReduce toolkit[32] and the Sorter is from HiBench benchmark suite.[33]

The input size of each application is 48GB. As the baseline case, we use "fsck" command to check the data placement of files and ensure that the ratio between the consumed HDD capacity and SSD capacity is approximately 1 to 1, which is consistent to the policy used by the current HDFS data placement policy. We submit the six jobs sequentially but within a short interval, such that each test has the same order of submission for a fair comparison.

Completion time. Figure 11(a) demonstrates the average completion times of the six applications under different placement and scheduling policies. In these tests, we enable all the optimization techniques in ASPS. As shown in the figure, ASPS reduces the average application completion time by 36% and 27% compared to Rand and Def on the heterogeneous cluster, respectively. The reason is that both Rand and Def are storage- and application-unaware, thus they are obviously inefficient for multiple jobs in a heterogeneous Hadoop cluster.



(a) Average I/O Throughput (b) Individual I/O Throughput

Fig. 12. I/O Throughputs of Applications.

Figure 11(a) also reveals that ASPS outperforms Stor. This is due to the fact that Stor only considers device heterogeneity but it ignores application I/O requirements. Thus, while Stor tries to place data of a job on the same type of devices and schedule the tasks of the job from the same types of devices, it does not consider how to make better utilization of the storage resources for multiple jobs. In contrast, ASPS can carry out cost-effective job execution for multiple applications by trying to place the data of applications with high I/O requirements on high-performance SSDs and to execute the tasks of these applications from the nodes with SSDs.

Figure 11(b) shows the completion time of each individual application. One can find that ASPS does not always outperform Stor in terms of individual application performance in multi-application cases. For example, ASPS increases the completion times of WordCount and GrepSearch compared to Stor. This is because ASPS treats them as applications with low I/O requirements and it leaves the chance of utilizing high-performance SSDs to other applications. According to the I/O metrics in section 3.3, only Sorter and TeraSort are I/O intensive applications and thus SSDs are reserved for these applications. As the rest of applications are insensitive to storage devices, their data placement and task scheduling prefer to HDDs. However, in terms of overall system performance, ASPS reduces the overall application completion time compared to Stor, Rand, and Def. This result indicates that ASPS is efficient for multi-application Hadoop cluster environments.

I/O throughput. Figure 12(a) demonstrates the average throughput of all applications in the above experiments. Similar to the previous tests, the result shows that ASPS can largely improve the average I/O throughput of the six applications relative to Rand, Def, and Stor. Compared to Def, ASPS improves the average I/O throughput by 9.3%. Figure 12(b) plots the I/O throughput of each individual application. One can find that with ASPS, some applications' throughputs are improved and some applications' throughputs are decreased relative to the other three approaches. However, the overall system throughput is still significantly enhanced.

6. Related Work

Data placement. Researchers have paid attention to optimize data placement of HDFS to improve Hadoop performance. VENU[14] uses SSDs as caches to place preferred data in the Hadoop system incorporating heterogeneous storage media. Triple-H[4] proposes a hybrid architecture to distribute data on heterogeneous storage resources on high-performance computing (HPC) clusters. NVFS[15] places performance-critical data on NVMs in a novel HDFS that utilizes NVM and remote direct memory access (RDMA). hatS[13] proposes a hybrid locality- and tier-aware data placement policy for HDFS with heterogeneous tiered storage devices. In Ref. 16, Xie et al. allocated a different number of blocks to nodes according to the node data processing capacity. The recent implementation of HDFS provides heterogeneous storage types in each data node.[23,24] However, these efforts focus on a single application while our work focuses on multiple concurrent applications. We also assume the CPU and memory resource are homogeneous and only the storage devices are heterogeneous in each data node.

Numerous efforts improve parallel program performance by optimizing the data placement of parallel file systems.[34,35] While these techniques are designed for HPC platform, our approach is designed for the Hadoop platform. Given the inherent differences between HPC and Hadoop architectures, such as network topology, data redundancy, etc., existing approaches in the HPC community cannot be simply applied to the Hadoop environment. This study efficiently addresses these challenges.

Task scheduling. Optimizing task scheduling is another effective approach to boost Hadoop performance. LATE scheduler optimizes backup tasks for straggler tasks to improve system efficiency.[17] SkewTune[18] breaks the atomic task into subtasks to gain data processing parallelism. Zacheilas et al. scheduled heterogeneous workloads onto heterogeneous nodes.[19] Tarazu[20] uses on-line trace and scheduling techniques to optimize the trade-off between parallelism of computing power and data transfer in a heterogeneous hardware environment. MROnline[21] schedules different resources for different applications according to their resource needs. Morpheus[27] utilizes dynamic resource reservations to mitigate execution variance. However, all these studies focus on CPU and data partition heterogeneity while our research focuses on storage and application heterogeneity. H-Scheduler[36] proposes a storage-aware scheduling approach in Spark clusters, but it is designed for multiple tasks of an application instead of multiple applications. In order to better optimize task scheduling of our research, many works in other heterogeneous environments are also worth studying.[37–40]

For scheduling of dependent jobs, such as workflow systems, task schedulers are proposed to optimize cost and makespan.[41,42]

For traditional scientific workloads, Ucar et al. presented a clustering task scheduling approach to assign tasks in heterogeneous computing systems.[43] This method considers task execution costs as well as communication costs between different tasks. However, this scheme focuses on HPC environments, while our approach is designed for Hadoop platforms.

Integrated approach. Some researchers use integrated approaches to boost Hadoop system performance. A closest related work is ϕSched,[22] which is a hardware-aware workflow scheduler for Hadoop. It treats a Hadoop deployment as a collection of multiple heterogeneous clusters, thus it examines the current cluster load along with data availability information to schedule the job to an appropriate cluster. In addition, ϕSched enhances the data placement of HDFS across a multi-cluster deployment, so that it can handle data locality as well as enable pre-staging of data to appropriate clusters as needed.

Our work differs from ϕSched in that we target one Hadoop cluster, where each node has heterogeneous storage devices but with homogeneous CPU and memory resources, while ϕSched focuses on multiple clusters, where different clusters have heterogeneous hardware. We also assume applications may have different I/O requirements when concurrently accessing a shared cluster.

7. Conclusions

In the big data era, heterogeneous application and storage become the trends in data centers. However, as one of the most popular big data processing frameworks, Hadoop has not efficiently updated in the face of such changes. This paper presents ASPS, a cooperative data placement and task scheduling approach for Hadoop clusters. ASPS relies on three key techniques: deriving application I/O requirements from a sampling method, placing application data according to application I/O requirements to better utilize fast devices, and scheduling application jobs based on I/O requirements and device types to achieve cost-effectiveness. We have validated our design and implementation with extensive tests in a Hadoop cluster. In the future, we plan to evaluate ASPS in a large-scale Hadoop cluster that is not currently available to us. We also intend to extend ASPS on other big data platforms and evaluate its effectiveness in practical environments.

Acknowledgments

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Response to Comments from Reviewers

We appreciate all detailed comments by JCSC reviewers, thank you for your hard work and valuable comments. We provide our responses as follows.

Reply to reviewer 1

1: There are a number of English grammatical, spelling, and/or usage errors, for examples:
- "meeting following challenge" → "facing the following challenges"
- Section header 2.2 "Motivation examples" → "Motivating Examples"

Response: Thanks for your reminder. We have corrected these errors and marked them with blue font in our revised manuscript.

2: Non-volatile memory is not mentioned.
Response: Thanks for your comment. The method proposed in our paper is general. The heterogeneous storage environment mentioned consists of a fast storage device and a slow storage device. It doesn't have to be HDD and SSD. Our design is also applicable for non-volatile memory, such as 3D Xpoint-based storage devices.

3: With so much of action shifting to Spark, it is not clear if improvements to Hadoop are of interest.
Response: Thanks for your comment. Yes, Spark is more and more popular but it can't completely replace Hadoop. In our paper, ASPS focuses on data storage optimization in the I/O path to improve system efficiency. Numerous existing Hadoop workloads can still benefit from ASPS, which can bring significant improvement to the community.

4: In some cases, however, applications may arrive dynamically and their characteristics may not be known ahead of time. This challenge is not considered in the paper.
Response: Thanks for your comment. MapReduce jobs are typically running in waves of tasks. Repetitive I/O characteristics can be found across waves of tasks. In each task, the I/O characteristics is also repetitive from iteration to iteration. ASPS utilizes this pattern to profile the I/O characteristics of unknown applications in the first multiple iterations of tasks or tasks of waves. This information can be accumulated to learn I/O requirements of more applications over time.

5: The experimental results section is unnecessarily lengthy, since results in Figures 6-9 are pretty obvious and could be explained/shown much more succinctly.
Response: Thanks for your comment. Mapper input placement and scheduling optimization, mapper output placement optimization, reducer input placement optimization and reducer output placement and scheduling optimization, they are different parts of our design and they bring performance improvements. We tested them separately to reveal the impact of these optimizations on the system, and the results are shown in Figures 6-9.

6: Never in the paper do the authors formally say which metric their approach tries to optimize. Is the average job execution time, the maximum job execution time? The results presented in the experimental section see to focus on the average job execution time, but the authors should state that is their objective.
Response: Thanks for your comment. In our paper, the objective of ASPS is to improve system efficiency by considering both application I/O requirements and storage device characteristics. For a single application, our approach tries to reduce the maximum job execution time. For

multiple applications, our approach tries to reduce the average job execution time. These are clearly stated in the paper.

7: I am not sure what Figures 6 and 7 show: apparently single application performance is being compared with and without the use of SSDs! The fact that use of SSDs results in better performance is obvious and is not really an evaluation of authors' methods.
Response: Thanks for your comment. We agree adding SSDs results in better performance. Therefore, we are not comparing purely HDD-based Hadoop with SSD-enhanced Hadoop. Def, Rand in the figures refer to default and random management of both drives on the same physical node, respectively. Stor in the figures refer to the method that placing data of a job in the same type of storage devices. Comparing ASPS with these three can demonstrate how efficiently ASPS utilizes the heterogeneity in storage devices to improve the performance.

Reply to reviewer 2

1: It looks like the existing data needs to be placed properly according to I/O requirement of the job before it starts to get the maximal benefit of ASPS. Please clarify this in the manuscript.
Response: Thanks for your comment. Yes, the existing data needs to be placed properly according to I/O requirement of the job before it starts to get the maximal benefit of ASPS, it is described clearly in the paper.

2: According to Section 3.4, the placer "first uses the network-aware policy to find the physical node that hosts an HDD and an SSD, and then it adopts the above rules to place the replica on the ultimate device, an SSD or an HDD, according to application characteristics". Does this mean only one device in each data node is utilized? Does this design lower the utilization of the storage devices which contradicts with the goal of this work?
Response: Thanks for your comment. In our design, we run two DataNodes simultaneously on the same machine and each DataNode manages one storage device. Both devices will be used at the same time, so there is no reduction in device utilization.

3: How does ASPS handle data dependency between jobs? Does it consider the potentially contradicting I/O requirements of dependent jobs? For instance, ASPS optimizes the placement of the output of job A. When job B launches to read the output, the placement might not be optimal for job B. Does ASPS reorganize the placement of output data offline to address this problem?
Response: Thanks for your comment. It is out of the scope of this paper. ASPS focuses on how to utilize the heterogeneity in the storage devices to better serve each individual application with different I/O characteristics. We will research it in the future work.

4: How does ASPS handle full disks? Since each data node has both SSD and HDD, how does ASPS mark a node out of storage space when either device is full or both are full?
Response: Thanks for your comment. In our design, we run two DataNodes simultaneously on the same machine and each DataNode still manages one storage device. So the storage device is full or not in ASPS has the same influence as the default Hadoop. So ASPS does not need a new mark strategy.

5: What is the relationship between Figure 6, 7, 8 and 9? Are they independent evaluation of each optimization, or evaluations of accumulated benefits of all optimizations? Please clarify the presentation.
Response: Thanks for your comment. Mapper input placement and scheduling optimization, mapper output placement optimization, reducer input placement optimization and reducer output placement and scheduling optimization, they are different parts of our design and they bring performance improvements. We tested them separately to reveal the impact of these optimizations on the system, and the results are shown in Figure 6, 7, 8 and 9.

6: What does the 'MapReduce' in Figure 10 mean? Does it mean the total execution time of the application? If that is the case, why the Def has a longer execution time compared to the results of previous tests (i.e., Figure 6 to 9) for the 4R case? It is not clear how many reducers are used in all tests.
Response: Thanks for your comment. In our paper, the default configuration of reducers is 4, it is described in the section 5.1. The 4R-Def in Figure 10 does not have a longer execution time compared to the Def in Figure 6 and 7. The 4R-Def in Figure 10 has a longer execution time compared to the Def in Figure 8 and 9 as we set the number of reducers to 16 in these two

tests, the sets are described in corresponding paragraphs.

7: How is fairness handled in ASPS? Is starvation possible in ASPS? Is it possible that all nodes are occupied by applications with high I/O requirements, which leads to starvation of applications with normal or low I/O requirements?
Response: Thanks for your comment. ASPS improves the performance by scheduling applications to the most suitable storage devices which can bring the most benefit. It does not change the order in the job queue, which keeps the fairness of the system intact. Thus, it will not lead to any starvation.

8: Please fix the typos and formatting errors, such as the big indent on page 19 and 20. The acronym HPC appears on line 5 of related work section, but it is introduced after that. The full name of acronym RDMA is never introduced.
Response: Thanks for your reminder. We have corrected these errors and marked them with blue font in our revised manuscript.

9: Job scheduling is effective in resource management. Could you provide some discussion of job scheduling on other aspects, like "Minimizing Cost and Makespan for Workflow Scheduling in Cloud using Fuzzy Dominance Sort based HEFT."
Response: Thanks for your comment. We have added some discussion of job scheduling on other aspects in our related works and marked it with blue font in our revised manuscript. Four papers have been added into the References:

Ref. 39 J. Li, G. Xie, K. Li, and Z. Tang, "Enhanced parallel application scheduling algorithm with energy consumption constraint in heterogeneous distributed systems", *Journal of Circuits, System and Computers* 2018 .

Ref. 40 J. Jiang, W. Li, L. Pan, B. Yang and X. Peng, "Energy optimization heuristics for budget-constrained workflow in heterogeneous computing system", *Journal of Circuits, System and Computers* **28** (09) 2019 .

Ref. 41 X. Zhou, G. Zhang, J. Sun, J. Zhou, T. Wei, and S. Hu, "Minimizing cost and makespan for workflow scheduling in cloud using fuzzy dominance sort based HEFT", *Future Generation Computer Systems*, vol. 93, pp. 278-289, 2019.

Ref. 42 P. Lu, G. Zhang, Z. Zhu, X. Zhou, J. Sun, and J. Zhou, "A review of cost and makespan-aware workflow scheduling in clouds", *Journal of Circuits, System and Computers* **28** (06) 2019 .

10: It is better to keep all the figure caption in single line. It is a little bit confusing when reading the captions.
Response: Thanks for your reminder. We have kept all the caption of subfigures in single line and marked them with blue font in our revised manuscript.

Reply to Editor

E1: It would be nice if you can cite some related work pubulished in JCSC recently.
Response: Thanks for your comment. According to your comments, we have reviewed some related work pubulished in JCSC recently and added the following references that are helpful to our work in our revised manuscript:

Ref. 39 J. Li, G. Xie, K. Li, and Z. Tang, “Enhanced parallel application scheduling algorithm with energy consumption constraint in heterogeneous distributed systems”, *Journal of Circuits, System and Computers* 2018 .

Ref. 40 J. Jiang, W. Li, L. Pan, B. Yang and X. Peng, “Energy optimization heuristics for budget-constrained workflow in heterogeneous computing system”, *Journal of Circuits, System and Computers* **28** (09) 2019 .

Ref. 42 P. Lu, G. Zhang, Z. Zhu, X. Zhou, J. Sun, and J. Zhou, “A review of cost and makespan-aware workflow scheduling in clouds”, *Journal of Circuits, System and Computers* **28** (06) 2019 .