A Constraint Programming Based Hadoop Scheduler for Handling MapReduce Jobs with Deadlines on Clouds

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ABSTRACT

A novel MapReduce constraint programming based matchmaking and scheduling algorithm (MRCP) that can handle MapReduce jobs with deadlines and achieve high system performance is devised. The MRCP algorithm is incorporated into Hadoop, which is a widely used open source implementation of the MapReduce programming model, as a new scheduler called the *CP-Scheduler*. This paper originates from the collaborative research with our industrial partner concerning the engineering of resource management middleware for high performance. It describes our experiences and the challenges that we encountered in designing and implementing the prototype CP-based Hadoop scheduler. A detailed performance evaluation of the CP-Scheduler is conducted on Amazon EC2 to determine the CP-Scheduler's effectiveness as well as to obtain insights into system behaviour and performance. In addition, the CP-Scheduler's performance is also compared with an earliest deadline first (EDF) Hadoop scheduler, which is implemented by extending Hadoop's default FIFO scheduler. The experimental results demonstrate the effectiveness of the CP-Scheduler's ability to handle an open stream of MapReduce jobs with deadlines in a Hadoop cluster.

Categories and Subject Descriptors

C.2.4 [**Computer-Communication Networks**]: Distributed Systems. C.4 [**Performance of Systems**]: *performance attributes, modeling techniques*.

Keywords

Resource management on clouds; MapReduce with deadlines; Hadoop scheduler; Constraint programming.

1. INTRODUCTION

Cloud computing has rapidly gained popularity and is now being used extensively by various types of users including enterprises as well as engineering and scientific institutions around the world. Some of the attractive features of the cloud that make it desirable to use include the "pay-as-you-go" model, scalability, and elasticity that lets a user dynamically increase or shrink the number of resources allocated. In cloud computing, hardware resources (including computing, storage, and communication), as well as software resources are exposed as on-demand services, and can be accessed by users over a network such as the Internet.

Cloud computing environments that provide resources on demand are of great importance and interest to service providers and consumers as well as researchers and system builders. Cloud service providers (e.g. Amazon) deploy large pools of resources that include computing, storage, and communication resources for consumers to acquire on demand. An effective resource management technique needs to be deployed for harnessing the power of the underlying resource pool, and efficiently provide resources on demand to consumers. Effective management of the resources on a cloud is also crucial for achieving user satisfaction and high system performance leading to high revenue for the cloud service provider. The important operations performed by a resource manager in a cloud include: *matchmaking* and *scheduling*. The matchmaking operation, when given a pool of requests, determines the resource or resources to be allocated to each request. Once a number of requests are allocated to a specific resource, a *scheduling* algorithm is used to determine the order in which each of the requests are to be executed for achieving the desired system objectives. Both matchmaking and scheduling are performed in a single step in Hadoop [1] by an entity referred to as the Hadoop scheduler in the literature [2]. A further discussion of Hadoop is provided in Section 2.2. Since such a single step operation is performed by the resource manager described in this paper, we refer to it as a Hadoop scheduler.

Two important components of *performance engineering* are performance optimization and performance modeling. One of the goals of this research is to engineer resource management middleware that can make resource management decisions that achieve high system performance, while also maintaining a low processing overhead. This paper describes how optimization theory and constraint programming (CP) [3] is used to devise a matchmaking and scheduling algorithm. Particular emphasis is placed on discussing our design and implementation experience and the performance implications of various system and workload parameters. CP is a well-known theoretical technique used to solve optimization problems, and is capable of finding *optimal* solutions with regards to maximizing or minimizing an objective function (see Section 2.1 for a further discussion).

A majority of the existing research on resource management on clouds has focused mainly on workloads that are characterized by requests requiring a best effort service. In this paper, workloads that comprise of requests with an associated quality of service often specified in a service level agreement (SLA) are considered. Most of the research on resource management for requests characterized by an SLA has only considered: (1) requests requiring service from a single resource and (2) a batch workload comprising a fixed number of requests. The focus of this research is on requests that need to be processed by multiple resources (called *multi-stage* requests) with SLAs specifying a required execution time, an earliest start time (release time), and an end-to-end deadline. Note that in line with the existing Hadoop scheduler [2], the earliest start time of a job is set to its arrival time in this research. Meeting an end-to-end deadline for requests that require processing by multiple system resources increases the complexity of the problem significantly. In addition, this paper considers a workload comprising an open stream of request arrivals (and not a workload with a fixed number of requests) that characterizes typical workloads on cloud data centres. Both the matchmaking and scheduling operations are well known to be computationally hard problems when they need to satisfy user requirements for a quality of service while also considering system objectives, such as high resource utilization and adequate revenue for the service provider.

A popular multi-stage application that is deployed by enterprises and institutions for processing and analyzing very large and complex data sets (for performing Big Data analytics for example) is *MapReduce* [4]. MapReduce, proposed by Google, is a programming model whose purpose is to simplify performing massively distributed parallel processing so that very large data sets can be processed and analyzed efficiently. In such cases, it is necessary to distribute the computation among multiple machines to facilitate parallel processing and reduce the total processing time. One of the benefits of MapReduce is that it provides an abstraction to hide the complex details and issues of parallelization. As its name suggests, the MapReduce programming model has two key functions [4]: *map* and *reduce.* The *map* function accepts a set of input key/value pairs and generates a new set of intermediate key/value pairs. These intermediary key/value pairs are grouped together and then passed to the reduce function, which is typically called the *shuffle* phase. The *reduce* function processes these intermediate key/value pairs to generally produce a smaller set of values.

A typical MapReduce application (or *job*) is comprised of multiple map tasks and multiple reduce tasks as illustrated in Figure 1. Reduce tasks cannot complete their execution until all the map tasks have finished. Many computations can be expressed using the MapReduce programming model. For example, a MapReduce application can be developed to process the logs of web servers to count the number of distinct URL accesses. This type of application is often referred to as a *WordCount* application. In this case, the input into the map function would be the logs of the web servers, and the map function would produce the following intermediate key/value pairs: {URL, 1}. This key/value pair indicates that one instance of a URL is found. Note that the intermediate data set may contain many duplicate key/value pairs (e.g. {www.google.com, 1} can appear multiple times). The reduce function sums all the values with the same key to emit the new data set: {URL, total count}.

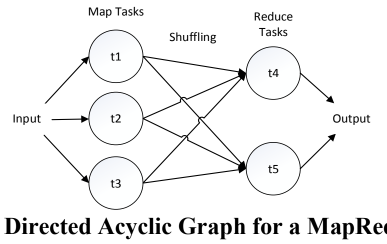


Figure 1. Directed Acyclic Graph for a MapReduce job.

More recently, resource management on clusters that execute MapReduce jobs with an associated completion time guarantee (deadline) has begun receiving attention from researchers (e.g., see [5] to [9]). Executing MapReduce jobs that have an associated end-to-end deadline is required for latency-sensitive applications such as live business intelligence, personalized advertising, spam/fraud detection, and real-time event log analysis applications [5]. By allowing users to specify deadlines, the system can also prioritize jobs and ensure that time-critical jobs are completed on time. Developing an efficient resource management middleware on such an environment is the focus of attention for this research performed in collaboration with our industrial partners Huawei, Canada.

More specifically, in this paper we focus on devising a scheduler for Hadoop [1] that can effectively perform matchmaking and scheduling of an open stream of MapReduce jobs with SLAs comprising an execution time for the map and reduce tasks, an earliest start time, and an end-to-end deadline. Hadoop is a widely used open source implementation of the MapReduce programming model (discussed in more detail in Section 2.2). The formulation of the matchmaking and scheduling problem of MapReduce jobs with SLAs is achieved using constraint programming (CP) as discussed in Section 3. In our preliminary work [10]**,** a detailed comparison of different resource management approaches based on CP as well as linear programming is presented. The results of the investigation showed the superiority of the CP-based approach implemented and solved using IBM ILOG CPLEX [11], including its more intuitive and simple formulation of constraints, lower processing overhead, and its ability to handle larger workloads.

In addition, our previous work [12] describes a novel *MapReduce Constraint Programming based Resource Management (MRCP-RM)* algorithm that can effectively perform matchmaking and scheduling of an open stream of MapReduce jobs with end-to-end deadlines. Using simulation a performance evaluation of MRCP-RM was conducted that demonstrated its effectiveness in generating a schedule where there is a low number of late jobs. The strong performance of MRCP-RM in simulation experiments has motivated this research that focuses on devising a *revised* version of the MRCP-RM algorithm and implementing the algorithm on a real system (i.e. Hadoop). A new CP-based Hadoop scheduler, named *CP-Scheduler*, which can handle matchmaking and scheduling an open stream of MapReduce jobs with deadlines is devised and implemented. To the best of our knowledge, there is no existing research describing a CP-based scheduler for Hadoop that can handle matchmaking and scheduling an open stream of MapReduce jobs with deadlines. The devising of the CP-Scheduler is based on the objective of providing user satisfaction while achieving high system performance. The main contributions of this paper include:

- A prototype CP-based Hadoop scheduler (called *CP-Scheduler)* for matchmaking and scheduling an open stream of MapReduce jobs with end-to-end deadlines.
  - o A discussion of our experiences and challenges that were encountered in designing and implementing the CP-Scheduler is provided.
- A detailed performance evaluation of the CP-Scheduler was conducted on Amazon EC2. Insights into system behavior and performance are described.
  - o This includes a discussion of the impact of various system and workload parameters on performance and a performance comparison of the CP-scheduler compared to an earliest deadline first (EDF) based Hadoop scheduler, which was implemented by extending Hadoop's default FIFO scheduler.
- Experimental demonstration of the effectiveness of the CP-Scheduler's ability to handle an open stream of MapReduce jobs with deadlines in a Hadoop cluster for a number of different workloads.

The results of this research will be of interest to researchers, cloud providers, as well as developers of resource management middleware for clouds and Hadoop-based systems.

The rest of the paper is organized as follows. In Section 2, background information is provided and related work is discussed. Section 3 discusses the problem formulation and how the MapReduce Constraint Program (MRCP) is devised. The focus of Section 4 is on the design and implementation of the Hadoop EDF and CP based schedulers, and includes a discussion of our experiences and challenges. In Section 5, the results of the experiments performed on Amazon EC2 to evaluate the EDF-Scheduler and CP-Scheduler are presented. Insights into system behavior and performance are described. Lastly, Section 6 concludes the paper and provides directions for future work.

2. BACKGROUND AND RELATED WORK

A brief overview of constraint programming (CP), Hadoop, and Amazon EC2 are provided in Sections 2.1 to 2.3, respectively. In addition, related research is discussed in Section 2.4.

2.1 Constraint Programming (CP)

CP is a theoretical technique for solving optimization problems that was developed by computer science researchers in the mid-1980s using knowledge from artificial intelligence, logic and graph theory, and computer programming languages [3]. A typical CP problem consists of three key parts: decision variables, objective function, and constraints. The *decision variables* are the variables in the CP problem that need to be assigned values. The *objective function* is a mathematical function that generates the value that needs to be optimized (i.e. minimized or maximized). Lastly, the *constraints* are a set of mathematical formulas that restrict the values that the decision variables can be assigned. In summary, when solving a CP problem, a solver will assign values to the decision variables that optimize the objective function, while ensuring that none of the constraints are violated.

2.2 Apache Hadoop

Apache Hadoop [1][13] is an open-source software framework (written in Java) that implements the MapReduce programming model, and is aimed at data-intensive distributed computing applications. Hadoop's software framework contains three sub-frameworks: Hadoop Common, Hadoop Distributed File System (HDFS), and Hadoop MapReduce. *Hadoop Common* provides utility functions including remote procedure call (RPC) and object serialization libraries. *HDFS* and *Hadoop MapReduce* are based on Google's MapReduce programming model [4] and Google's File System (a distributed file system implementation), respectively.

A typical Hadoop cluster comprises a single *master* node and one or more *slave* nodes. In Hadoop 1.2.1, which implements the MapReduce version one (MRv1) architecture, the master node comprises of two entities (which are often called *Hadoop daemons*): *NameNode* and *JobTracker*. Each slave node also consists of two Hadoop daemons: a *DataNode* and a *TaskTracker*. The NameNode and DataNodes are the Hadoop daemons in charge of managing HDFS. Each file that is written to HDFS is split into blocks (64MB by default) and each block is stored on the storage device where a DataNode is running. Each block is replicated multiple times (by default three times) and stored on different DataNodes. It is the job of NameNode to keep track of which DataNode stores the blocks of a particular file (which is called the *metadata* of the HDFS). Another important function of NameNode is to direct DataNodes (slaves) to perform HDFS I/O operations (read, write, delete). DataNodes keep in constant contact with NameNode to receive I/O instructions.

JobTracker is the link between user applications and the Hadoop cluster. In addition, JobTracker is the Hadoop daemon responsible for managing TaskTrackers. Some of the main responsibilities of JobTracker include: initialize jobs and prepare them for execution, determine when the map and reduce tasks of jobs should be executed and which TaskTrackers should execute them (i.e. perform matchmaking and scheduling), as well as monitor all tasks that are currently running. TaskTrackers function as the JobTracker's slaves, and their primary purpose is to execute the map or reduce tasks that they are assigned. Another responsibility of TaskTracker is to periodically send polling/ update messages (called *heartbeats*) to JobTracker. If JobTracker does not receive a heartbeat message from a TaskTracker within a specified time period (by default one minute), JobTracker will assume that the TaskTracker has been lost, and re-map all the tasks that was assigned to the lost TaskTracker.

2.3 Amazon EC2

Amazon Elastic Compute Cloud (abbreviated Amazon EC2) is a public cloud that provides Infrastructure-as-a-Service (IaaS). Amazon EC2 allows consumers to launch virtual machines (VMs) called *instances*. After launching these instances, consumers can connect to the instance, and deploy and run their own applications. Amazon EC2 also provides various *instance types*, which are pre-configured VMs that have various predetermined CPU, memory, storage, and networking capacity. The cost of running the instance depends on the type of instance deployed, and users are charged by the hour. As expected, Amazon EC2 provides the benefits of cloud computing including elasticity (scale up/scale down computing capacity dynamically), and pay-as-you-go (no upfront investment).

2.4 Related Work

The focus of this research is on developing resource management techniques for handling MapReduce applications, which are used by many companies and institutions to facilitate Big Data analytics [14]. A representative set of related work is provided next.

In [15] a MapReduce framework for heterogeneous and load-imbalanced environments is described. The research presented in [16] and [17] focuses on a formulation of the MapReduce matchmaking and scheduling problem using linear programming. In these works, the objective is to find a schedule that minimizes the completion time of jobs in the cluster. In [5] the authors present a resource allocation policy based on earliest deadline first (EDF) that attempts to allocate to each job the minimum number of task slots required for completing the job before its deadline. Dong et al. [6], describe a technique that can handle scheduling of MapReduce workloads that contain best-effort jobs as well as jobs with deadlines. Similar to [5], the proposed technique executes jobs at their minimum degree of parallelism to meet its deadline (i.e. attempts to use all of a job's slack time). Mattess et al. [7], propose an approach that uses a cloud to dynamically provision resources to execute MapReduce jobs that cannot meet their deadlines on a local set of resources. Investigation of resource management algorithms for minimizing the cost of allocating virtual machines to execute MapReduce applications with deadlines is presented in [8]. The authors of [9] describe an execution cost model for MapReduce that considers the following job attributes: execution time of the map and reduce tasks, and the size of input data. A scheduler for Hadoop that could handle scheduling a fixed number of jobs was developed based on this concept.

The approaches described in [15], [16], and [17] do not consider jobs with end-to-end deadlines and focus on other aspects of MapReduce jobs. Furthermore, the works described in [5] to [9], which do consider MapReduce jobs with deadlines, use heuristic-based techniques for matchmaking and scheduling the jobs. Handling of workloads comprising an open stream of MapReduce jobs with deadlines is not considered by [6] to [9], which the CP-Scheduler can effectively handle. The existing default schedulers for Hadoop that handle a fixed number of resources do not consider jobs with deadlines. To the best of our knowledge, no existing paper has proposed a CP-based Hadoop scheduler that can effectively perform matchmaking and scheduling of an open stream of MapReduce jobs with end-to-end deadlines on a cluster with a fixed number of processing resources, which is described in this paper.

3. MAPREDUCE CONSTRAINT PROGRAM (MRCP)

The MapReduce Constraint Program (MRCP) is a model of the MapReduce matchmaking and scheduling problem formulated using constraint programming. MRCP was discussed in full detail in our previous work [10]. In this section, a brief summary of MRCP is provided, along with a discussion of the new modifications made in this paper to improve MRCP and make it work with Hadoop. The objective of MRCP is to meet SLAs while achieving high system performance.

Table 1 shows the formulation of the improved MRCP. The inputs required include: a set of MapReduce jobs, J and a set of resources, R, on which to map J. Each job j in J has the following: an earliest start time (s_j), a set of map tasks (T_j^{mp}), a set of reduce tasks (T_j^{rd}), and a deadline (d_j). The tasks t in each job has an estimated execution time in seconds (e_t), and resource capacity requirement (q_t) that specifies the number of resources the task requires to execute (typically set to one for most map and reduce tasks). Note that the estimated task execution times includes the time required to read the input data, and exchange data (e.g. intermediate keys) between the map and reduce phases. The resources are modelled after Hadoop's TaskTrackers. Each resource r in R has a map task capacity (no. of map slots), c_r^{mp}, and a reduce task capacity (no. of reduce slots), c_r^{rd}. The map and reduce task capacity specifies the number of map tasks and reduce tasks, respectively, that the resource can execute in parallel simultaneously.

The decision variables of MRCP are outlined below. Note that the set T contains the tasks for all the jobs in J.

- *Matchmaking, x_{tr}*: a binary variable. If task t is assigned to resource r, x_{tr}=1, otherwise x_{tr}=0. Each task t in T has an x_{tr} variable for each resource r in R
- *Scheduling, a_t*: an integer variable. Each task t in T, has an a_t variable that specifies the assigned start time of t.
- N_j: a binary variable. If a job j misses its deadline N_j is set to one. Each job j in J has an N_j that is initialized to zero.
- C_j (new): an integer variable that stores the completion time of job j. Each job j in J has a C_j variable.

The objective function of MRCP has been modified from previous work that focused only on the minimization of late jobs. The first part of the objective function minimizes the number of late jobs; whereas, the second part of the objective function minimizes the maximum turnaround time of all jobs. The net effect of the second part of the objective function is to distribute the tasks more evenly among the resources (i.e. load balancing). This is confirmed to be achieved by examining the output schedule generated after MRCP is solved.

A summary of the purpose of each of MRCP's constraints outlined in Table 1 is provided. Constraint (1) states that each task t in the set of tasks, T, can only be assigned to one resource. The second constraint ensures that each job's map task has an assigned start time that is after the job's earliest start time. Constraint (3) enforces that each job's reduce tasks are scheduled to start after all of the job's map tasks are completed. The fourth constraint, which is a new constraint that was not described in previous work states that the completion time of the job is set to the completion time of the job's latest finishing reduce task. Constraint (5) makes sure that N_j for all the jobs that miss their deadlines is set to one. The next two constraints (6) and (7) are the resource capacity constraints, and enforce that the map and reduce task capacities of each resource are not violated at any point in time. Note that constraints (6) and (7) make use of CP's global constraint function *cumulative*. Lastly, constraints (8)-(10) specify the valid values that the decision variables can be assigned.

Table 1. MapReduce Constraint Program (MRCP)

$$Minimize\left(\sum_{j\in J} N_j+1\right)\times max_{j\in J}(C_j-s_j)$$

$$such\ that$$

$$\sum_{r\in R} x_{tr}=1 \quad \forall\, t\in T \tag{1}$$

$$(a_t\geq s_j \quad \forall t\in T_j^{mp}) \quad \forall\, j\in J \tag{2}$$

$$\left(a_{t'} \geq \max_{t\,\in\, T_j^{mp}} (a_t+e_t) \quad \forall t' \in T_j^{rd}\right) \forall j\in J \tag{3}$$

$$\left(C_j=\max_{t\,\in\, T_j^{rd}} (a_t+e_t)\right) \forall j\in J \tag{4}$$

$$(C_j>d_j \ \Rightarrow N_j=1) \quad \forall j\in J \tag{5}$$

$$\begin{aligned}(cumulative((a_t|x_{tr}=1),(e_t|x_{tr}=1),(q_t|x_{tr}=1),\\ c_r^{mp})\ \forall t\in T_j^{mp})\forall r\in R\end{aligned} \tag{6}$$

$$\begin{aligned}(\,cumulative((a_t|x_{tr}=1),(e_t|x_{tr}=1),(q_t|x_{tr}=1),\\ c_r^{rd})\ \forall t\in T_j^{rd})\,\forall r\in R\end{aligned} \tag{7}$$

$$(x_{tr}\in\{0,1\} \quad \forall\, t\in T)\ \ \forall r\in R \tag{8}$$

$$N_j\in\{0,1\} \quad \forall\, j\in J \tag{9}$$

$$a_t\in\mathbb{Z} \quad \forall\, t\in T \tag{10}$$

3.1 Implementing and Solving MRCP

The software chosen to solve MRCP is *IBM ILOG CPLEX Optimization Studio v12.5* [11] (abbreviated CPLEX). CPLEX is used because in our preliminary work [10] it was found that it was the most effective (had lower overhead and able to handle larger workloads) in solving MRCP. Before MRCP can be solved by CPLEX's CP solving engine, called the *CP Optimizer* [18], MRCP needs to be implemented (modelled) using CPLEX's *Optimization Programming Language* (OPL) [11]. OPL is an algebraic language that is specifically designed for developing and expressing optimization models. Note that the implementation of MRCP using OPL is referred to as the *OPL model*.

4. HADOOP EDF-SCHEDULER AND CP-SCHEDULER

As indicated in Section 1, a Hadoop scheduler performs both matchmaking and scheduling. This section discusses the design and implementation of two new Hadoop schedulers that can handle matchmaking and scheduling of an open stream of MapReduce jobs with deadlines. The first is the earliest deadline first scheduler, *EDF-Scheduler*, which was devised by extending Hadoop's default FIFO scheduler (see Section 4.2). The second is a more advanced constraint programming based scheduler, called *CP-Scheduler* (see Sections 4.3-4.4), that performs matchmaking and scheduling by solving MRCP, which was discussed in Section 3.1. Our experiences and challenges in implementing these schedulers are discussed. The main challenge encountered is understanding the Hadoop source code and determining which of the Hadoop classes need to be modified to implement the schedulers. A summary of the challenges encountered is provided.

- Determining the Hadoop classes that need to be modified to: (1) support user-specified job deadlines (discussed in Section 4.1), and (2) allow users to define the estimated task execution times of their jobs (see Section 4.3.2).
- Determining how to implement a custom scheduler for Hadoop's JobTracker (see Section 4.2.1). Examining the source code of Hadoop's default FIFO scheduler to learn the intricacies of how job scheduling in Hadoop is performed (discussed in Section 4.2.2).
- The main challenges of implementing the Hadoop CP-Scheduler include: (1) determining how to create the input data for MRCP from Hadoop classes (see Section 4.3.1), (2) integrating IBM CPLEX into Hadoop (see Section 4.3.3), (3) investigating how to handle IBM CPLEX's lack of support for `long` values to represent timestamps (see Section 4.4.2 and 4.3.1), and (4) developing an approach to ensure that a specific TaskTracker executes the task it has been assigned in the MRCP solution (see Section 4.4.1).
- During testing a bug was discovered where the reduce tasks would stall and take a very long time to complete (discussed in Section 4.4.1.1).

4.1 Adding Support for Job Deadlines in Hadoop

This section discusses the Hadoop classes that were modified to support user-specified job deadlines. First, in Hadoop's `org.apache.hadoop.mapred.JobInProgress` class a new private field, `long deadline`, was added to store a job's deadline. The value stored in the deadline field represents the number of milliseconds elapsed from midnight, January 1, 1970 UTC. The `JobInProgress` (JIP) class represents a MapReduce job that is being tracked by JobTracker. The JIP class maintains all the information for a MapReduce job including: the job's map and reduce tasks, its state (e.g. running, succeeded, failed), as well as accounting information (e.g. launch time and finish time). JIP's deadline field is initialized via the JIP constructor by invoking `conf.getJobDeadline()` where `conf` is an object that is an instance of the `org.apache.hadoop.mapred.JobConf` class, and `getJobDeadline()` is a new method that was implemented in the `JobConf` class to retrieve the job's deadline.

The `JobConf` class represents a MapReduce job configuration. It is an interface for users to specify the properties (e.g. job name and number of map and reduce tasks) for their MapReduce job before submission to the Hadoop cluster. Two new methods are added to the `JobConf` class: `getJobDeadline()` and `setJobDeadline()`. The method `setJobDeadline(long deadline)` sets the job configuration property, `mapred.job.deadline`, to the supplied parameter. Similarly, the `getJobDeadline()` method is used to retrieve the value assigned to the `mapred.job.deadline` property.

The last Hadoop class that needs to be modified to support user-specified job deadlines is the `org.apache.hadoop.mapreduce.Job` class. The `Job` class is the main user API that is used to create and submit jobs to the Hadoop cluster (more specifically JobTracker). The `Job` class is the user's view of the MapReduce job, and it provides methods to allow the user to create, configure, and submit a job, as well as control its execution, and obtain status information (e.g. state of the job). Similar to the `JobConf` class, the two new methods added to the `Job` class are: `setJobDeadline()`, and `getJobDeadline()`. These two methods in turn invoke `conf.setJobDeadline()` and `conf.getJobDeadline()`, respectively, where `conf` is an instance of a `JobConf` object. Note that `conf` is one of the private fields of the `Job` class and is initialized when a `Job` object is created. The sequence of calls for setting the deadline of a job is illustrated in the sequence diagram shown in Figure 2.

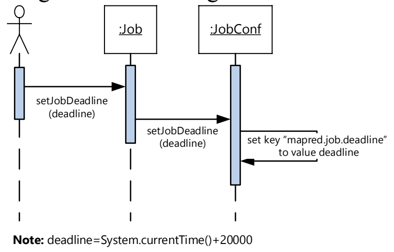

:Job
:JobConf
setJobDeadline (deadline)
setJobDeadline (deadline)
set key "mapred.job.deadline" to value deadline
Note: deadline=System.currentTime()+20000

Figure 2. Sequence diagram for `setJobDeadline()`.

4.2 Hadoop EDF-Scheduler

An earliest deadline first scheduler called *EDF-Scheduler* is implemented by extending Hadoop's default FIFO (first-in-first-out) scheduler. This is done to investigate if the naïve solution of using the commonly known EDF policy is effective for handling an open stream of MapReduce jobs with deadlines (see Section 5). This section briefly discusses the key classes that were modified to implement the EDF-Scheduler, but first an overview of how to implement a custom scheduler for Hadoop is discussed in Section 4.2.1, and in Section 4.2.2, a discussion of the key classes of Hadoop's FIFO Scheduler is provided.

4.2.1 Implementing a Custom Hadoop Scheduler

Hadoop provides a pluggable scheduler framework [2] that allows developers to implement custom schedulers using their own scheduling logic and algorithms. The key to implementing a custom scheduler for Hadoop is to extend Hadoop's abstract class `org.apache.hadoop.mapred.TaskScheduler` and implement the abstract method `List<Task> assignTasks(TaskTracker tt)`. The `assignTasks()` method returns a list of tasks (including both map and reduce tasks) that the supplied `TaskTracker` should execute as soon as it receives the list. Note that the returned list can be empty meaning that there are no new tasks to assign to the `TaskTracker` at the moment.

The Hadoop `org.apache.hadoop.mapred.JobTracker` class implements the Hadoop JobTracker daemon, which is responsible for scheduling the tasks of the MapReduce jobs that are submitted. The `JobTracker` class has a `TaskScheduler` private field named `taskScheduler` which stores the reference to the scheduler (e.g. FIFO, EDF or CP) that is used to assign and schedule tasks on TaskTrackers. More specifically, the `JobTracker` class invokes `taskScheduler.assignTasks()` each time JobTracker receives and processes a heartbeat message from a TaskTracker (i.e. within the `JobTracker` class' `heartbeat()` method). Recall that heartbeats are the periodic status messages that TaskTrackers send to JobTracker.

4.2.2 Hadoop FIFO Scheduler

Hadoop's default FIFO scheduler is implemented in the `org.apache.hadoop.mapred.JobQueueTaskScheduler` class (abbreviated JQTS), which extends Hadoop's `TaskScheduler` abstract class. The JQTS class keeps jobs that are ready to execute in priority order and by default, this order is FIFO. There are two other key classes required by JQTS: (1) `JobQueueJobInProgressListener` (JQ-JIPL) and (2) `EagerTaskInitializationListener` (ETIL). The JQ-JIPL class represents the job queue manager, and by default, it sorts the jobs in the queue in FIFO order, but it is possible to implement a custom ordering strategy such as EDF. JQ-JIPL extends Hadoop's abstract class `JobIn`

`ProgressListener` (JIPL), which is a class that is used by the `JobTracker` class to listen for when a job's lifecycle in JobTracker changes. The JIPL class has three key methods: `jobAdded()`, `jobRemoved()`, and `jobUpdated()`, which are invoked when JobTracker sees that a job is added, removed, or updated, respectively. For example, when a user submits a job to JobTracker, JQ-JIPL's `jobAdded()` method is invoked by the `JobTracker` class to add the submitted job to JQ-JIPL's queue.

The ETIL class prepares a submitted job for execution by initializing/creating the job's tasks. A thread pool with four worker threads is deployed by the ETIL class to concurrently initialize jobs. Similar to JQ-JIPL, the ETIL class also extends the JIPL abstract class. Thus, as soon as a job is submitted to JobTracker, ETIL places the submitted job into its job initialization queue called `jobInitQueue` (sorted using FIFO by default). The job remains in the queue until there is a worker thread available to initialize the job.

4.2.3 *Implementation of Hadoop EDF-Scheduler*

The EDF-Scheduler is implemented in a class called `EDF_Scheduler` (stored in the package `org.apache.hadoop.mapred`), and is based closely on the implementation of Hadoop's FIFO scheduler (discussed in Section 4.2.2). The major changes that are made are in the JQ-JIPL and ETIL classes. More specifically, in the ETIL class the `resortInitQueue()` method is modified to sort the queue with priority given to the jobs with an earlier deadline (i.e. earliest deadline first). Moreover, the JQ-JIPL class' `JobSchedulingInfo` *Comparator* was also modified to place jobs with an earlier deadline first. In Java, a `Comparator` is an interface used by Java collection objects to sort elements of the collection in a specified order. The `JobSchedulingInfo` is a *static nested class* of JQ-JIPL that assembles all the necessary job-related information (e.g. job id and deadline) for the EDF-Scheduler to schedule jobs.

4.3 Hadoop CP-Scheduler

Figure 3 shows an overview of the CP-Scheduler being deployed on a Hadoop cluster. There is a single master node and *m* slave nodes (defined in Section 2.2). Users submit jobs to JobTracker which uses the CP-Scheduler to schedule the jobs onto TaskTrackers. CP-Scheduler uses three IBM CPLEX Java library packages (discussed in Section 4.3.3), and performs matchmaking and scheduling by creating a MRCP OPL model and using CPLEX's CP Optimizer (a CP solving engine) to solve the OPL Model (discussed in detail in Section 4.4).

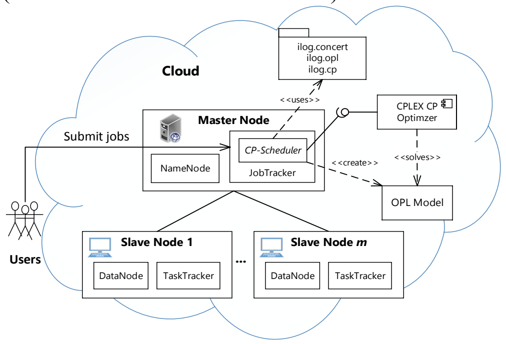


Figure 3. Overview of a Hadoop cluster deploying the CP-Scheduler.

Similar to the EDF-Scheduler the implementation of the *CP-Scheduler* starts with creating a class, called `CP_Scheduler` (in the package `org.apache.hadoop.mapred`) which extends Hadoop's `TaskScheduler` abstract class. In addition, The CP-Scheduler also has two classes: `JobQueueManager` and `JobInitializer` that extend Hadoop's JIPL class, and have similar functionality as the EDF-Scheduler's JQ-JIPL and ETIL classes, respectively.

4.3.1 *Entity Classes*

The `CP_Scheduler` class also uses three entity classes: `Job_CPS`, `Task_CPS`, and `Resource_CPS`. These classes represent how the CP-Scheduler views MapReduce jobs, tasks, and TaskTrackers (resources), respectively, and stores the necessary information required by MRCP (discussed in Section 3) for scheduling the MapReduce tasks onto TaskTrackers. An abbreviated class diagram showing the important attributes and methods of the three entity classes is presented in Figure 4. Note that a discussion of the key attributes and methods of the `CP_Scheduler` class is provided in Section 4.3.

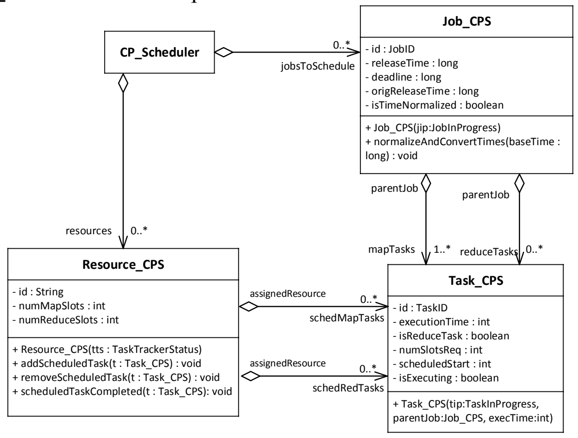


Figure 4. Class diagram (abbreviated) of CP-Scheduler's entity classes.

The `Job_CPS` class contains information required by the `CP_Scheduler` to map jobs onto TaskTrackers (resources). This information is retrieved from Hadoop's `JobInProgress` class, and includes the job's: id, release time, deadline, map tasks, and reduce tasks. Note that both the release time and deadline fields store the number of milliseconds elapsed from midnight, January 1, 1970 UTC. Since the release time field is constantly updated depending on when the job is being scheduled (discussed in Section 4.4), the `origReleaseTime` field stores the time of when the job is first received by JobTracker. The `isTimeNormalized` field indicates if the following calculations have been performed: `releaseTime = releaseTime – REFERENCE_TIME`, and `deadline = deadline - REFERENCE_TIME` (referred to as *time normalization*). `REFERENCE_TIME` is a field in the `CP_Scheduler` class that stores a timestamp which is taken when the CP-Scheduler maps a job for the first time. The job's release time and deadline have to be normalized because CPLEX does not support values of type `long` (only `int` is supported). Normalization of the times is discussed in more detail in Section 4.4.2.

The `Task_CPS` class holds the information that the `CP_Scheduler` uses for matchmaking and scheduling tasks including: the task's id, estimated execution time (in seconds), task type, and the number of slots (resource capacity) required. This information, except the estimated task execution times (discussed in Section 4.3.2), is retrieved from Hadoop's `TaskInProgress` class. Once a task has been mapped, its `assignedResource` and `scheduledStart` fields are initialized to the resource that the task is scheduled to execute on, and the time the task is to start running, respectively. The `isExecuting` field is set to true if the task is currently executing.

The `Resource_CPS` class contains TaskTracker information (retrieved from Hadoop's `TaskTrackerStatus` class), including:

id, the number of map slots, and the number of reduce slots. The tasks that are assigned to the resource are placed in either the `schedMapTasks` list or the `schedRedTasks` list, depending on the task type. Note that both these lists keep tasks sorted by earliest scheduled start time. The methods `addScheduledTask()` and `removeScheduledTask()` are used to add, and remove tasks from the scheduled tasks lists, respectively. The last method, `schedTaskCompleted()`, is called when a task has completed its execution. Completed tasks are moved from the scheduled tasks lists to the completed tasks lists.

4.3.2 Adding Support for Estimated Task Execution Times

One of the inputs that MRCP (discussed in Section 3) requires is the estimated task execution times. Note that the estimation of task execution times can be accomplished by analyzing historical data such as system logs, and workload traces of previously executed tasks (discussed in Section 5.1.2). Similar to how support for job deadlines was added to Hadoop (discussed in Section 4.1), support to allow users to specify the estimated task execution times of their submitted jobs is accomplished by adding two new methods: `setEstimatedTaskExecutionTimes()` and `getEstimatedTaskExecutionTimes()` (abbreviated setET and getET, respectively) to Hadoop's `Job` and `JobConf` classes.

The setET method accepts two parameters: a comma delimitated string of task execution times in seconds (e.g. "2,2,3"), and the task type (map or reduce). Depending on the task type, the setET method assigns either the `mapred.job.mapTask ExecTimes` property or the `mapred.job.reduceTaskExecTimes` property to the supplied string. The getET method accepts a single parameter the task type (map or reduce), and returns a string array containing the values assigned to the corresponding property.

4.3.3 Integration of IBM CPLEX

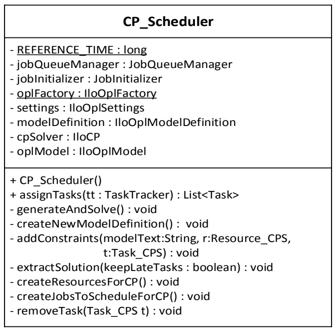
As discussed in Section 3.1, MRCP is solved using IBM CPLEX. Therefore, to model and solve MRCP, the CP-Scheduler requires importing IBM CPLEX's Java libraries to make use of the following Java APIs [11]: *ILOG Concert Technology* (abbreviated *Concert*), *ILOG OPL*, and *ILOG CP*. These APIs allow the CP-Scheduler to embed CPLEX's CP Optimizer solving engine and the MRCP OPL model into the `CP_Scheduler` class. To use these APIs, the following CPLEX Java library packages need to be imported: `ilog.concert`, `ilog.opl`, and `ilog.cp`.

Before being able to import the required CPLEX Java libraries, IBM CPLEX v12.5 was installed on the machine where the master node executes. The IBM CPLEX v12.5 JAR (Java archive) file, named `oplall12.5.jar`, was placed in Hadoop's `/hadoop/lib` folder. In addition, a modification is made to Hadoop's `/hadoop/bin/hadoop` script so that the JobTracker would be able to locate the CPLEX libraries. More specifically, the `java.library.path` variable of the `hadoop` script is modified to include the folder `<IBM_CPEX_Install_dir>/opl/bin/x86-64_sles10_4.1`.

Two additional classes that are used by the `CP_Scheduler` for aiding in the integration of CPLEX are: `OPLModelSource` and `OPLModelData`. The former stores the implementation of MRCP written in CPLEX's Optimization Programming Language (OPL), which is referred to as the *OPL model*. The latter class is used by the `CP_Scheduler` class to create the input data for the OPL model. `OPLModelData` extends the OPL APIs `ilog.opl.Ilo CustomOplDataSource` class [11] and converts the `CP_Scheduler`'s *resources* and *jobsToSchedule* lists to a format that the OPL model can read (i.e. generates the OPL model's input sets: *Jobs*, *Tasks*, and *Resources*).

4.4 CP-Scheduler Algorithm

This section provides details on the *CP-Scheduler* algorithm. A class diagram of the `CP_Scheduler` showing its key fields and methods is presented in Figure 5. Note that these fields and methods are discussed in Sections 4.4.1-4.4.3.



```
CP_Scheduler
- REFERENCE_TIME : long
- jobQueueManager : JobQueueManager
- jobInitializer : JobInitializer
- oplFactory : IloOplFactory
- settings : IloOplSettings
- modelDefinition : IloOplModelDefinition
- cpSolver : IloCP
- oplModel : IloOplModel
+ CP_Scheduler()
+ assignTasks(tt : TaskTracker) : List<Task>
- generateAndSolve() : void
- createNewModelDefinition() :  void
- addConstraints(modelText:String, r:Resource_CPS,
                 t:Task_CPS) : void
- extractSolution(keepLateTasks : boolean) : void
- createResourcesForCP() : void
- createJobsToScheduleForCP() : void
- removeTask(Task_CPS t) : void
```

Figure 5. Abbreviated class diagram of CP_Scheduler.

4.4.1 assignTasks()

Table 2 shows the CP-Scheduler algorithm which is implemented in the `CP_Scheduler` class' `assignTasks()` method. The input required by the algorithm is a TaskTracker to assign tasks to. The algorithm returns a list of tasks for the supplied TaskTracker to execute (includes both map and reduce tasks). The first step (line 1) is to calculate the currently available map and reduce slots of the supplied TaskTracker (e.g. `availMapSlots = mapCapacity – runningMaps`). The next step (lines 2-3) is to create the `Resource_CPS` list (called `resources`) and `Job_CPS` list (called `jobsToSchedule`), which are required as input to the OPL model. The `createResourcesForCP()` method (abbreviated CR) invokes the `JobTracker` class' `activeTaskTrackers()` method to return a collection of `TaskTrackerStatus` (TTS) objects. The CR method then uses the TTS objects to create `Resource_CPS` objects via its constructor (recall Figure 4). The `createJobsToSchedule ForCP()` method (abbreviated CJ) checks the `JobQueueManager`'s `jobQueue` (a collection of `JobInProgress` objects) for new jobs in the *running* state (i.e. setup is complete and tasks are initialized), and creates a new `Job_CPS` object for each one. If there are new jobs or resources, the `CP_Scheduler`'s `hasNewJob` and `hasNewResources` flags are set to true.

The next step is to check if `CP_Scheduler`'s `jobsToSchedule` list is empty. If this condition is true, then an empty task list is returned (line 4). If either `hasNewJobs` or `hasNewResources` flags are true `CP_Scheduler`'s `generateAndSolve()` method (discussed in Section 4.4.2) is invoked (see lines 5-7). The two flags are used to prevent unnecessarily invoking `generateAndSolve()`when a MRCP solution for the same input (jobs and resources) has already been found. Once a solution is found, the next step (line 8) is to retrieve the assigned map and reduce tasks from the `Resource_CPS` object in `resources` (named `res`) that has the same id as the supplied `TaskTracker`.

In lines 9-19, each available map slot of the supplied `TaskTracker` is assigned the map task with the earliest scheduled start time. This is accomplished by first retrieving the task (a `Task_CPS` object) from `res`, as well as retrieving the task's corresponding `TaskInProgress` (TIP) (lines 10 and 11). Before assigning the task, TIP is checked to see if the task has completed, and if true, the `CP_Scheduler`'s `removeTask()` method is invoked (lines 12-13). The `removeTask()` method performs a number of operations including: moving the task from its assigned resource's scheduled tasks list to the completed tasks list, and moving the task from its parent job's tasks to schedule lists to the completed task lists. Recall that a task's assigned resource and parent job are

`Resource_CPS` and `Job_CPS` objects, respectively. Furthermore, `removeTask()` also checks if the job's `mapTasks` and `reduceTasks` lists are empty (i.e. job has completed executing). If this is true, the job's release time is reset to its original release time, and the job is moved from the `CP_Scheduler`'s `jobsToSchedule` list to the `completedJobs` list. Otherwise, if the task has not completed executing, the task is assigned to a TaskTracker for execution (lines 14-18). This is accomplished by invoking a new method named `obtainSpecificMapTask()` (abbreviated OSMT) that is implemented in Hadoop's `JobInProgress` class. As the name suggests, given a `TaskInProgress` object, OSMT returns the corresponding `Task` object (i.e. Task that has the same id). The task that is returned by OSMT is added to the `assignedTasks` list.

Table 2. CP-Scheduler algorithm (implemented in `CP_Scheduler::assignTasks()`).

```
Input: TaskTracker tt
Output: List of Tasks for the supplied TaskTracker to execute,
named assignedTasks.
1:  Get currently available map and reduce slots of tt.
2:  call createResourcesForCP()
3:  call createJobsToScheduleForCP()
4:  if no jobs to schedule return empty list
5:  if new jobs to schedule or new resources in cluster then
6:      call generateAndSolve()
7:  end if
8:  res ← get Resource_ CPS object from resources with same
    id as tt
9:  for each available map slot in tt do
10:     Task_CPS t ←get scheduled map task with earliest start
            time from res
11:     tip ← t.getTaskInProgress()
12:     if tip is complete then
13:         call removeTask()
14:     else
15:         jip ← t.getParentJob().getJobInProgress()
16:         call jip.obtainSpecificMapTask(tip) returning
                                                mapTask
17:         Add mapTask to assignedTasks.
18:     end if
19: end for
20: Repeat lines 9 to 19 but this time for reduce slots and
        reduce tasks with one change to Line 14: the new
        condition is "else if all map tasks of t's parent job are
        completed then"
21: return assignedTasks
```

Next, the same logic is executed for the `TaskTracker`'s reduce slots (line 20), except with one change to the *else* statement (line 14). The *else* statement is changed to an *else if* statement, which checks if all the map tasks of the job has completed before assigning reduce tasks (see Section 4.4.1.1). A new `obtainSpecificReduceTask()` method is implemented in `JobInProgress` that returns the reduce task (`Task` object) with the same id as the supplied TIP. Lastly, the `assignedTasks` list which now contains the tasks that the supplied `TaskTracker` should execute is returned (line 16).

4.4.1.1 Reduce Task Stalling Problem

During preliminary testing it was found that in some situations the reduce tasks of a job *j* would take a very long time to complete because its map tasks were not being executed in a timely fashion. This can be caused, for example, when the CP-Scheduler schedules the map tasks of a job with an earlier deadline before *j*'s tasks. It was observed that the reason *j*'s reduce task could not finish executing is because not all of *j*'s map task were finished executing. In fact, it was discovered that Hadoop permits reduce tasks of a job to start executing once a few of its map tasks have finished executing (and does not wait until all the job's map tasks have completed).

One approach to solve this problem is to give execution priority to all of *j*'s map tasks so that they can execute before other tasks. Initially, this approach was used, and implemented by adding constraints to the OPL model that stated that these task should be scheduled to execute at their originally scheduled times (and not be rescheduled). However, further testing showed that this solution is not ideal when it comes to minimizing the number of late jobs because jobs that have an earlier deadline may have to wait for execution. On the other hand, a problem with not ensuring that *j*'s reduce tasks can complete its execution in a timely manner, is that *j*'s reduce tasks will remain idle and unnecessarily consume reduce task slots of TaskTrackers. This can in turn also delay the execution of jobs that already have their map tasks completed. The solution that was used to avoid these problems is to prevent the CP-Scheduler from assigning reduce tasks to TaskTrackers until all the job's map tasks are completed (recall Section 4.4.1). This guarantees that reduce tasks assigned to a TaskTracker can complete its execution.

4.4.2 generateAndSolve()

Table 3 presents CP-Scheduler's `generateAndSolve()` algorithm whose purpose is to generate the MRCP OPL model, and solve it. The first step is to initialize the `CP_Scheduler`'s `REFERENCE_TIME` (abbreviated *RT*) if it has not already been done, and initialize the `mrcpCurrentTime` variable to zero (line 1-3). Recall that *RT* is required to normalize the `Job_CPS`' release time and deadline fields as discussed in Section 4.3.1. If *RT* has already been initialized, then the `mrcpCurrentTime` variable is set to the current time minus *RT*, and the value is converted into seconds (lines 4-7). As the name suggests, `mrcpCurrentTime` is the current time value used when solving MRCP. Recall from Section 4.3.1 that OPL does not support values of type `long`.

Table 3. CP-Scheduler algorithm, `generateAndSolve()`.

```
Input: none. Output: none.
1:  if REFERENCE_TIME = -1 then
2:      REFERENCE_TIME ← System.currentTimeMillis()
3:      mrcpCurrentTime ← 0
4:  else
5:      mrcpCurrentTime ← System.currentTimeMillis() –
                          REFERENCE_TIME
6:      Convert mrcpCurrentTime to seconds.
7:  end if
8:  for each job j in jobsToSchedule do
9:      call j. normalizeAndConvertTimes (REFERENCE_
10:                                           TIME)
11:     if mrcpCurrentTime > j.getReleaseTime() then
            j.setTempReleaseTime(mrcpCurrentTime )
12: end for
13: call createNewModelDefinition()
14: Create a new OPL model and attach the data source
        containing jobsToSchedule and resources.
15: Generate and solve the OPL model.
16: call extractSolution()
```

In the next steps (lines 8-12), each job (a `Job_CPS` object) in `CP_Scheduler`'s `jobsToSchedule` list has its release time and deadline normalized by invoking `Job_CPS`' `normalizeAndConvertTimes()` method (discussed in Section 4.3.1). In addition, each job's release time is updated to `mrcpCurrentTime` because a job cannot start before `mrcpCurrentTime`. In line 13, a new OPL model definition is created by invoking `CP_Scheduler`'s `createNewModelDefinition()` method, which is discussed in Section 4.4.3. After a new model definition has been created, a new OPL model is produced (line 14), and then solved (line 15) using CPLEX. After a solution is found, it is extracted by invoking `CP_Scheduler`'s `extractSolution()` (line 16). This method retrieves values from MRCP's decision variables: x_{tr} and a_t (discussed in Section 3), and assigns the values to the `Task_CPS` objects' `assignedResource` and `scheduledStart` fields, respectively. In addition, the tasks (`Task_CPS` objects) that are assigned to a particular resource *r* (a `Resource_CPS` object) are added to *r's* `scheduledMapTasks` or `scheduledRedTasks` lists depending on its task type.

4.4.3 createNewModelDefinition()

Table 4 presents the `CP-Scheduler`'s `createNewModel Definition()` algorithm. The first step is to initialize the variable `modelSrc` with a string value containing the OPL model's source code, which is obtained from `OPLModelSource` (discussed in Section 4.3.3) The next step is to process all scheduled tasks (`Task_CPS` objects) to check the state of the task's corresponding `TaskInProgress` (TIP) object (lines 2 to 11). If the task's TIP state is *running* then the `Task_CPS`' `isExecuting` field is set to true, and the `CP_Scheduler`'s `addConstraints()` method is called (line 11). This method, as the name suggests, adds a new constraint to `modelSrc` that specifies the assigned start time, end time, and assigned resource of the task that is currently executing. The purpose of the new constraint is to prevent the solver from scheduling new tasks on the same resource slot during the same time interval. In addition, the task's `isExecuting` field is also set, which will be passed on to the OPL model (via `OPLModelData` class), to tell the CP solver that enforcing Constraint 2 is not required for tasks that are already executing. Conversely, if the task's TIP state is *completed* then the `CP_Scheduler`'s `remove Task()` method (discussed in Section 4.4.1) is invoked (line 9). The final step (line 13) is to create the new OPL model definition object from the updated OPL model source, `modelSrc`.

Table 4. CP-Scheduler algorithm, `createNewModelDefinition()`.

```
Input: none. Output: none.
1:  modelSrc ← OPLModelSource.getSource()
2:  for each resource r in resources do
3:      for each task t in r.getAllScheduledTasks() do
4:          tip ← t.getTaskInProgress()
5:          if tip is currently executing then
6:              t.setCurrentlyExecuting(true)
7:              call addConstraints(modelSrc, t, r)
8:          else if tip is finished executing then
9:              call removeTask(t)
10:         end if
11:     end for
12: end for
13: modelDefinition ← Create new OPL model definition using
        the updated OPL model source, modelSrc.
```

5. PERFORMANCE EVALUATION

This section describes the experiments that were conducted to evaluate the performance of the CP-Scheduler and EDF-Scheduler developed for Hadoop. In addition, a discussion of the experimental results and insights into system performance and behavior are provided.

5.1 Experimental Setup

5.1.1 System

The experiments were performed on an Amazon EC2 Hadoop cluster comprising one master node, and four slave nodes configured to have one map and one reduce slot each. Recall from Section 2.2 and Figure 3 the definitions of the master and slave nodes. Each node is an Amazon EC2 `m3.medium` instance. The m3.medium instances are *fixed performance instances* that provide a good balance of compute, memory, and network resources. Each m3.medium instance is launched with a 2.5GHz Intel Xeon E5-2670 v2 (Ivy Bridge) CPU, 3.75 GB of RAM, and runs Ubuntu 13.04. The cost of running an m3.medium instance is $0.07 per hour. Our experiments were performed on this cluster because it allowed us to confirm the functionality of the new prototype Hadoop CP-Scheduler by viewing the output of JobTracker and each TaskTracker in real-time. In addition, the chosen cluster fits within our current experimental budget. For future work, the plan is to perform experiments on a cluster with more nodes.

Initially, our experiments used Amazon's `t2` instances; however, it was discovered that t2 instances are susceptible to performance degradation over time if the CPU usage is continuously high. This is because t2 instances are *burstable performance instances* and do not provide a fixed (consistent) performance. The t2 instances continuously receive *CPU Credits* at a fixed rated depending on the instance size. A CPU Credit supplies the instance with the performance of a full CPU core for one minute. If the instance is idle, it accumulates CPU Credits whereas the instance consumes CPU Credits when it is active. As a result of this, the `m3.medium` fixed performance instances are used in the experiments.

5.1.2 Workload

A Hadoop `WordCount` application (as discussed in Section 1) with three different input data sizes (i.e. *job size*) were used in the experiments: *small*: 3 files (~3MB), *med:* 10 files (~5MB), and *large*: 20 files (~10MB), to investigate the impact of different workload sizes on the performance of the system. The files are e-books (in plain text format) that are obtained from Project Gutenberg (www.gutenberg.org). Note that each job size has a number of map tasks that corresponds to the number of files it has, and one reduce task. For example, the medium workload job comprises ten map tasks and one reduce task. In these experiments, our goal is to use workloads with real input data, which is why e-books from Project Gutenberg were chosen. The number of files in each job was selected so that the cluster could execute the MapReduce job within a reasonable amount of time (small: ~50s, med: ~80s, large: ~100s) when there is no contention for resources. The reasonable execution time of these jobs results in a reasonable run time when conducting experiments with an open stream of job arrivals. The Hadoop/MapReduce framework is used with a variety of different data intensive applications. These include Big Data applications as well as applications processing data with sizes of 10s of megabytes (see [19] for example). This is in line with the size of data files we have experimented with. Analyzing the performance of the CP-Scheduler with other workloads characterized by large volumes of data forms a direction for future research.

A `JobSubmitter` (which runs on its own m3.medium instance) was implemented in Java to submit an open stream of WordCount jobs at a specified *arrival rate* (λ) to the Amazon EC2 Hadoop cluster. The arrival of jobs was generated using a Poisson process. The earliest start time (s_j) of the jobs is equal to its arrival time, and the job's deadline (d_j) is calculated as the sum of s_j and the maximum execution time of the job multiplied by an execution time multiplier (e_m). The purpose of e_m is to give the job slack time, and it is generated using a uniform distribution within the interval [1, 5]. These parameters for the jobs are generated in a similar manner to [5]. Note that the sample execution times of the jobs are obtained by performing a dry run—executing the jobs on the cluster when there is no resource contention.

Four different types of experiments were performed and each experiment type was conducted for the CP-Scheduler as well as for the EDF-Scheduler. In the first three experiment types, the `JobSubmitter` was configured to submit only a single job type: small, medium, or large. In the fourth experiment type, the `JobSubmitter` submits a mix of the three job types with each job type having an equal probability of being submitted. Note that the `JobSubmitter` is initialized with a predetermined seed for its random number generator so that the same sequence of jobs is submitted during the CP-Scheduler experiments and EDF-Scheduler experiments. Each experiment was run for at least five hours so that the system reached steady state.

5.1.3 Performance Metrics

The performance metrics that are considered in each experiment to evaluate the effectiveness and performance of the schedulers include:

- *Proportion of late jobs (P):* calculated as the ratio of the number of late jobs (*N*) and the number of jobs executed (*NE*). Recall that a job *j* is considered late if its completion time (C_j) is after its deadline (d_j).
- *Average job turnaround time* (*T*): calculated as $\sum_{j \in J}(C_j - s_j)$ divided by *NE*.
- *Average matchmaking and scheduling time of a job* (*O*): calculated as the total time required to perform matchmaking and scheduling of jobs during an experiment divided by *NE*. Note that *O* is a measure of the schedulers' processing overhead.

5.2 Experimental Results

5.2.1 Mixed Workload

Figure 6 and Figure 7 demonstrate that CP is able to effectively handle a complex workload with different types of jobs. CP outperforms EDF by a large margin in terms of *P* (up to 91%) and *T* (up to 57%). The CP-Scheduler is able to effectively interleave the execution of the tasks of multiple jobs such that jobs do not miss their deadlines. The EDF-Scheduler's poor performance in terms of *P* and *T* can be attributed to its focus on only scheduling a single job at a time (i.e. the job with the earliest deadline), and not interleaving the execution of jobs.

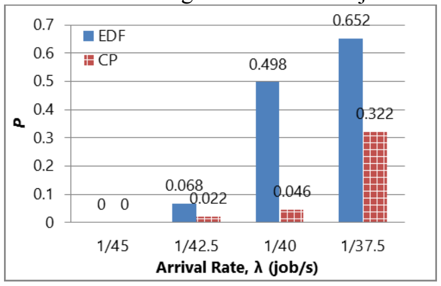


Figure 6. Mixed Workload: *P*.

The results in Figure 7 show that CP's *O* is larger (changing from 590ms to 3.5s as λ increases), compared to EDF's *O* which remains close to 12ms for all λ. CP's *O* is higher and is observed to increase with λ because the CP-Scheduler requires generating an OPL model that represents MRCP, and solving the OPL model using IBM's CP Optimizer (see Section 4.4). When there are more jobs in the OPL model's input, more time is required to generate and solve the OPL model because of the higher number of decision variables and constraints that need to be processed by the CP Optimizer. On the other hand, EDF's *O* tends not to change significantly with λ because the EDF-Scheduler selects the job to schedule by retrieving the first job in its job queue (i.e. the job with the earliest deadline). Although, CP's *O* is high, the *O*/*T* ratio which is an indication of a scheduler's processing overhead in relation to the average job turnaround time, is still relatively low in all cases (less than 0.393%).

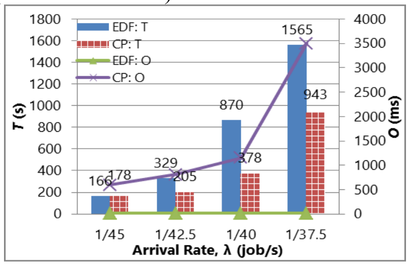


Figure 7. Mixed Workload: *T* and *O*.

5.2.2 Small Workload

The experimental results using the small workload are presented in Figure 8 and Figure 9. As shown in Figure 8, CP achieves a much lower *P* compared to EDF. When λ<1/17.5job/s it is observed, that CP achieves a *P* of less than 0.07 which is close to the lower bound of zero. At 1/22.5 job/s *P* is zero for both systems; however, at higher arrival rates CP outperforms EDF and is observed to have a 100% decrease in *P*. At λ=1/15 job/s, both systems exhibit a high *P* due to high system load (average utilization of resources is 0.92) resulting in a high contention for resources. However, CP still has an approximately 50% lower *P* compared to EDF. As discussed, the lower *P* and *T* of CP can be attributed to MRCP interleaving the execution of jobs to minimize the number of late jobs; whereas, EDF simply schedules the job with the earliest deadline.

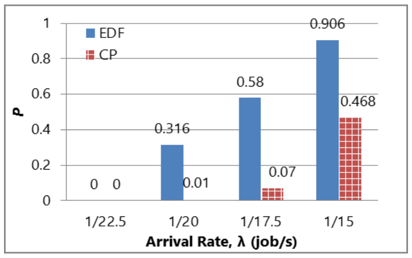


Figure 8. Small Workload: *P*.

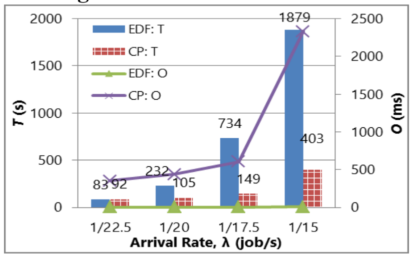


Figure 9. Small Workload: *T* and *O*.

Figure 9 shows that CP's *T* is up to 80% lower than EDF's *T*, except for when λ=1/22.5 job/s. At the lowest arrival rate, CP has a slightly higher (10%) *T* because of its higher *O*. When focusing on *O* it is observed that EDF achieves a much lower *O* compared to CP. EDF's *O* is approximately 5ms for all λ, whereas CP's *O* increases with λ, changing from 350ms to 2.3s. As discussed, the reason for CP's higher *O* is due to the processing overhead of having to generate and solve MRCP. In comparison to the EDF-Scheduler, the CP-Scheduler puts more effort into deciding which jobs to map in order to minimize *P*. The benefits of this are captured in the superior performance demonstrated by CP with its lower *P* while still maintaining an *O*/*T* ratio of less than 0.6%.

5.2.3 *Medium Workload*

Due to the longer execution times of the jobs resulting in a higher load on the system, the λ values used in these experiments are lower than those used for the small workload. Similar to the results of the small workload, CP achieves up to 100% lower *P* compared to EDF (see Figure 10). In fact, it is observed that CP outperforms EDF by a larger margin when using the medium workload (88% on average) compared to the small workload (78% on average). This shows that the CP-Scheduler is capable of handling jobs with a higher number of tasks more effectively.

In Figure 11, performance trends that are similar to the small workload results are observed: CP has lower *T* but a higher *O* compared to EDF. As expected, the *O* for both the schedulers increase when compared to the small workload case due to the higher number of map tasks in each job. EDF's *O* increases from 5ms (from the small workload) to approximately 10ms in the medium workload for all λ. On the other hand, CP's *O* changes from 1.1s to 1.5s as λ increases for the medium workload, compared to 0.3s to 2.3s when the small workload is used. The only case where using the small workload (compared to the medium workload) resulted in a higher *O* for CP is when λ is at its highest value (1/15 job/s for the small workload and 1/37.5 job/s for the medium workload). This can be attributed to the small workload case having a higher system load (average resource utilization, *U* is 0.92) compared to the medium workload case where *U* is 0.89.

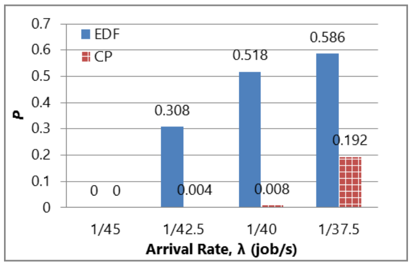


Figure 10. Medium Workload: *P*.

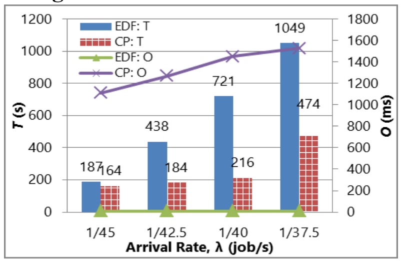


Figure 11. Medium Workload: *T* and *O*.

Another difference between the medium and small workload results is observed when analyzing the cases where *P*=0 (i.e. λ =1/22.5 job/s for the small workload, and λ=1/45 job/s for the medium workload). In the medium workload case, CP achieves a lower *T* compared to EDF, but in the small workload case, the opposite is true. This can be attributed to the fact that in the small workload case, the CP-Scheduler can quickly determine a schedule that minimizes *P* (the primary objective) without focusing on *T* (*O*=352ms). Conversely, for the medium workload case, the CP-Scheduler needs to ensure jobs are executed in a more timely manner in order to minimize *P* (*O*=1.1s).

5.2.4 *Large Workload*

The results of the large workload (see Figure 12 and Figure 13) show CP's largest performance improvement in terms of *P* and *T* over EDF. In all cases, CP is able to achieve a *P* of zero; even when λ= 1/70 job/s where the *P* that EDF achieves is 0.49. Furthermore, CP's performance improvement in terms of *T* is observed to increase from 32% to 100% as λ increases. The cause of the poor performance of EDF is due to the larger workload comprising jobs with more tasks, which results in longer job execution times. Since the EDF-Scheduler does not interleave the execution of jobs, scheduling jobs that have more tasks tends to lead to more late jobs because multiple jobs with closer deadlines can arrive on the system during the execution of the initial job. This shows that the EDF-Scheduler is more suited to handle a fixed number of jobs (closed workload) and cannot effectively handle an open stream of job arrivals. The CP-Scheduler, on the other hand, does interleave the execution of jobs and always attempts to create a new schedule that minimizes the number of late jobs when new jobs arrive on the system.

The performance trend of *O* when using the large workload is similar the other workloads. CP's *O* (which increases from 529ms to 765ms with λ) is higher than EDF's *O* (approximately 16ms for all λ). It is observed that EDF's *O* increases with the size of the workload because larger workloads comprise jobs with more tasks, and more time is required to map a job with a higher number of tasks compared to a job with fewer tasks. This shows that EDF's *O* has a direct relationship with the number of tasks in a job (called the *job size*). Conversely, CP's *O* does not show a similar trend when the size of the workload increases. CP's *O* depends on the job size, but is also influenced by λ. This can be seen by comparing the results of the medium and large workloads. For all values of λ experimented with, CP's *O* is observed to be higher for the medium workload in comparison to the large workload. This can be attributed to the higher system load. More specifically, in the medium workload the average resource utilization (*U*) varies from 0.74 to 0.89 as λ increases from 1/45 to 1/37.5 jobs/s, compared to the large workload where *U* changes from 0.34 to 0.37 as λ increases from 1/77.5 to 1/70 jobs/s. Note that the values of *U* in the large workload case are lower because of the lower values of λ used in the experiments.

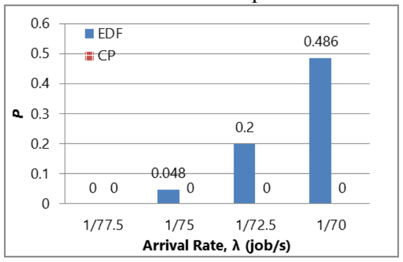


Figure 12. Large Workload: *P*.

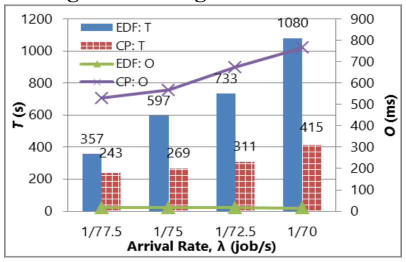


Figure 13. Large Workload: *T* and *O*.

6. CONCLUSIONS AND FUTURE WORK

The focus of this paper is on engineering resource management middleware that can effectively handle matchmaking and scheduling an open stream of MapReduce jobs with SLAs each of which is characterized by an execution time, an earliest start time, and an end-to-end deadline. The key objective of this research is to achieve high system performance while minimizing resource management overhead. More specifically, a MapReduce constraint programming based matchmaking and scheduling algorithm (MRCP) is devised and solved using IBM CPLEX. Furthermore, a new constraint programming based scheduler for Hadoop, which is a popular open source implementation of the MapReduce programming model, is devised and implemented. The new scheduler for Hadoop, called *CP-Scheduler*, generates and solves an MRCP model to perform matchmaking and scheduling of an open stream of MapReduce jobs with deadlines. Our experiences and the challenges that we encountered in devising the CP-Scheduler and implementing the algorithm in Hadoop are described in this paper. A performance evaluation of the CP-scheduler is conducted on an Amazon EC2 cluster running Hadoop and its performance is compared with that of an EDF-Scheduler, which is implemented by extending Hadoop's default FIFO scheduler. The experimental results demonstrate the CP-Scheduler's effectiveness to map an open stream of MapReduce jobs with deadlines in a Hadoop cluster. Some of the key insights into system behaviour and performance are summarized:

- In all the experiments, the CP-Scheduler generated a schedule that leads to a lower or equal P compared to the EDF-Scheduler, and close to the lower bound of zero when the system utilization is reasonable. The best performance observed is in the large workload experiments where the CP-Scheduler generated a P of zero in all cases. In other experiments, the percentage improvement of the CP-Scheduler's P compared to the EDF-Scheduler's P is observed to be as low as 48% and as high as 100%.
- In most cases, the CP-Scheduler generated a schedule with a lower T compared to the EDF-Scheduler. The CP-Scheduler is outperformed by the EDF-Scheduler by a small margin when the system is lightly loaded (i.e. small workload and small arrival rate, which can be attributed to the CP-Scheduler's O having a larger impact on T.
- Although, the CP-Scheduler demonstrates a much superior P and T in comparison to EDF-Scheduler, this performance improvement is accompanied by an increase in O. However, it is still observed that the ratio O/T for the CP-Scheduler is still very small in all cases experimented with (less than 0.69%).
    - The CP-Scheduler's O depends on the number of tasks in a job (i.e. job size), as well as the job arrival rate, and thus for a given workload type O increases as the job arrival rate increases. Conversely, the EDF-Scheduler's O increases with job size, and remains relatively the same as job arrival rate increases.

Overall, the experimental results show that the CP-Scheduler can effectively perform matchmaking and scheduling of an open stream of MapReduce jobs with deadlines in a Hadoop cluster leading to a schedule with a small proportion of late jobs. The EDF-Scheduler; however, seems to be more suited to handle a fixed (closed) workload because of the fact that it does not interleave the execution of jobs, which can lead to very poor performance on an open system. This can happen, for example, when the execution times of jobs are long and multiple jobs arrive on the system with earlier deadlines (see Section 5.2.4).

For future research, we plan to perform more extensive experiments, which includes experiments that use larger workloads and more nodes. Moreover, techniques for estimating task execution times and handling errors associated with the estimated times warrants further investigation.

7. ACKNOWLEDGMENTS

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