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Stochastic Workload Scheduling for Uncoordinated Datacenter Clouds with Multiple QoS Constraints

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Abstract—Cloud computing becomes a well-adopted computing paradigm. With the unprecedented scalability and flexibility, the computational cloud is able to carry out large scale computing tasks in the parallel fashion. The datacenter cloud is a new cloud computing model that use multi-datacenter architectures for large scale massive data processing or computing.
In datacenter cloud computing, the overall efficiency of the cloud depends largely on the workload scheduler, which allocates clients' tasks to different Cloud datacenters. Developing high performance workload scheduling techniques in Cloud computing imposes a great challenge which has been extensively studied. Most previous works aim only at minimizing the completion time of all tasks. However, timeliness is not the only concern, while reliability and security are also very important. In this work, a comprehensive Quality of Service (QoS) model is proposed to measure the overall performance of datacenter clouds. An advanced Cross-Entropy based stochastic scheduling (CESS) algorithm is developed to optimize the accumulative QoS and sojourn time of all tasks. Experimental results show that our algorithm improves accumulative QoS and sojourn time by up to 56.1% and 25.4% compared to the baseline algorithm, respectively. The runtime of our algorithm grows only linearly with the number of Cloud datacenters and tasks. Given the same arrival rate and service rate ratio, our algorithm steadily generates scheduling solutions with satisfactory QoS without sacrificing sojourn time.

Index Terms—Cloud Computing, DataCenter Clouds, Quality of Service, Workload Scheduling

1 Introduction

Cloud computing [1], which delivers computing as a service, has emerged as a well-adopted computing paradigm which offers vast computing power and flexibility, and an increasing number of commercial cloud computing services are deployed into the market such as Amazon EC2 [2], Google Compute Engine [3], and Rackspace Cloud [4]. The new computing paradigms of "Cloud of Clouds" [5] and "datacenter clouds" [6], [7] are a creation of federated Cloud computing environment that coordinates distributed datacenter computing and achieves high QoS for Cloud applications. Large-scale data-intensive applications across distributed modern datacenter infrastructures is a good implementation and use case of the "Cloud of Clouds" paradigm. A good example for data-intensive analysis is the field of High Energy Physics (HEP). The four main detectors including ALICE, ATLAS, CMS and LHCb at the Large Hadron Collider (LHC) produced about 13 petabyes of data in 2010 [8]. This huge amount of data are stored on the Worldwide LHC Computing Grid that consists of more than 140 computing centers distributed across 34 countries. The central node of the Grid for data storage and first pass reconstruction, referred to as Tier 0, is housed at European Organization for Nuclear Research (CERN). Starting from this Tier, a second copy of the data is distributed to 11 Tier 1 sites for storage, further reconstruction and scheduled analysis.

Since the datacenter cloud computing paradigm offers massive computational resources, it provides enormous opportunities for software designers to architect their software in order to benefit from the massive parallelism. After a customer submits a computational job to a cloud, task scheduling will be performed to decide where, when and how this job can be executed. On the other hand, cloud computing features the high degree of the information heterogeneity which includes different processor speed, different processor location, different processor energy consumption, different job waiting time, different job runtime, different communication cost as well as other uncertainties. Among these, the security and reliability are highly important [9], [10]. These introduce significant technical difficulty in designing a high performance task scheduling framework. Therefore, it is necessary to have a comprehensive Quality of Service (QoS) metric to quantify the performance of a scheduler. Since the scheduler allocates computational tasks to heterogeneous computational resources for optimizing QoS, it is called a QoS aware task scheduler in cloud computing.

Our contributions are summarized as follows.

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- A comprehensive QoS model for evaluating the overall performance of the datacenter Cloud is proposed. Our QoS model provides different metrics, measuring the Cloud computing performance from different angles. It guarantees satisfying performance of the datacenter Cloud in terms of not only timeliness, but also reliability and security.
- A QoS driven Cross-Entropy based stochastic scheduling (CESS) algorithm is developed to optimize the scheduling solution in terms of every metric defined in the QoS model.
- The CESS algorithm improves accumulative QoS and sojourn time by up to 56.1% and 25.4% compared to the baseline algorithm, respectively.
- The CESS algorithm runs efficiently. The runtime scales only linearly with the number of jobs and the number of Cloud datacenters. Therefore, it has the potential to be successfully deployed in the real world.
- Given the same arrival rate and service rate ratio, our CESS algorithm steadily generates scheduling solutions with satisfactory QoS without sacrificing sojourn time.

2 Backgrounds and Related Work

2.1 Cloud of Clouds

A computing Cloud [11], [12] is a set of network enabled services, providing scalable, QoS guaranteed, normally personalized, inexpensive computing infrastructures on demand, which can be accessed in a simple and pervasive way [13], [14], [15].

The paradigm of "Cloud of Clouds", or InterCloud [16], [17], [18], [19], [20], [21], is to leverage the global infrastructure based on multiple Clouds for large scale distributed applications. The multi-datacenter infrastructure [22], [23], a reference implementation of the "Cloud of Clouds" model, implements a global infrastructure across distributed datacenters, storage services or clusters for intercloud applications.

Current research on the "Cloud of Clouds" model includes the programming model & software architecture [24], security & storage service [25], and inter-cloud computing standards [26]. In our previous research we have implemented a programming model for the paradigm of "Cloud of Clouds" by developing the G-Hadoop system [6], [7], a software framework for MapReduce applications across distributed datacenters and clusters.

2.2 Datacenter Clouds

Datacenter Clouds typically refers to the software and hardware infrastructures that provides general-purpose high-performance computing capabilities [27]. Different from conventional distributed systems such as large scale computer clusters, a datacenter Cloud is composed of distributed computer centers or datacenters from multiple geographical locations across the world [28]. In general, datacenters in clouds can communicate with each other via high-speed network interface. With this distributed infrastructure, a single computational task can be carried out on multiple machines in the parallel fashion, with the efficiency significantly improved.

Datacenter clouds promise on-demand access to affordable large-scale resources in computing and storage (such as disks) without substantial upfront investment. Thus it is naturally suitable for processing big data, especially streaming data, via allowing data processing algorithms to run at the scale required for handling uncertain data volume, variety, and velocity.

However, to support a complicated, dynamically configurable big data ecosystem, we need to innovate and implement novel services and techniques for orchestrating cloud resource selection, deployment, monitoring, and QoS control [5], [29].

The paradigm of datacenter Cloud computing has the following features

- Resource Sharing A Virtual Organization (VO) refers to a dynamic set of individuals and/or organizations bounded by the same set of resource-sharing rules and conditions. Here the resource includes not only data represented in various formats, but also computational power and storage units. They are requested and shared by a wide range of computational tasks from clients in industry, as well as academia. It becomes a technical challenge to coordinate resource sharing among the dynamic virtual organizations [30].
- Site Autonomy Resources shared in datacenter Clouds are commonly owned and controlled by different individuals or organizations in different sites [31], [32], [33]. Administrators of each site decide which resource to share and how to share the resources. Therefore, clients of the datacenter Cloud may experience different scheduling policies and security mechanisms when using datacenter Clouds.
- Hierarchy and Uncoordinated Local Queue Management
  In each geographical site, there may be a local resource management system, e.g., PBS [34], [35] and Sun Grid Engine [36]. Cloud users cannot access the individual resources inside the sites. Cloud users submit tasks to the Global Resource Management System (GRMS). Subsequently, GRMS submits tasks to the Local Resource Management System (LRMS) [37], [38]. The LRMS schedules the tasks to the resources inside local resource system. GRMS and LRMS constitute hierarchical datacenter Cloud environments.
  The uncoordinated LRMS may lead a large variety of queueing policies and queue waiting time, which will make significant impact on Cloud data processing applications. For example, the statistical analysis [39] shows that the queue wait time of Cloud systems, such as World LHC Computing Grid (WLCG), is random and highly complicated to predict.
- Heterogeneity
  Datacenter Clouds a highly heterogeneous environment [40], [41]. Different sites may have different types of resources. Even the resources of the same type, located at different sites, may have different

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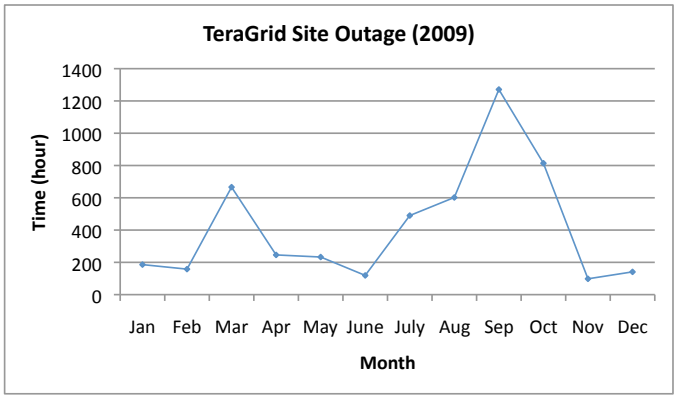

Fig. 1: Outage statistic of TeraGrid in 2009

configurations, capacities and performance.

- Large-Scale Distribution
  As discussed above, datacenter Cloud enables resource sharing among geographically distributed sites. These sites are connected via traditional network interface. Network communication delay may be extremely high when some communication intensive applications are running among these sites. In this scenario, network performance has an important effect on resource management [42], [43].
- Frequent Site Outrage
  The resources in Cloud datacenters could become unavailable during a site outage due to various reasons, such as power supply failure, scheduled maintenance, or hardware failure. As shown in Figure 1, during the year 2009, there were approximately 290 outages with total 5,000 hours on the TeraGrid infrastructures of datacenters and computer centers. On average, a single site experienced the outage time around 4% of the time duration of the year 2009. Apparently, site outages can seriously jeopardize the performance of the datacenter Clouds.

2.3 Multi-Cluster computing

The Multi-Cluster computing paradigm [44] employs multiple distributed clusters to build large computing infrastructure for HPC applications. There have been a considerable portion of research devoted to the multi-cluster scheduling, for example, scheduling of workflow applications [45], [46], [47] and scheduling of independent tasks [48], [49], [50] across the multi-cluster infrastructure. Compared with the aforementioned work, our research in this paper is devoted to scheduling of MapReduce jobs to multiple clusters, where we use a different task model and the data-centric scheduling heuristic.

The Gfarm file system [51] is a distributed file system designed to share vast amounts of data between globally distributed clusters connected via a wide-area network. Similar to HDFS the Gfarm file system leverages the local storage capacity available on compute nodes. In our work, we use Gfarm file system as a global distributed file system that supports the MapReduce framework.

In our G-Hadoop implementation, we use the Torque [52] as a cluster resource manager. The Distributed Resource Management Application API (DRMAA) [53] is a high-level API specification for the submission and control of jobs to one or more cluster resource managers. In G-Hadoop implementation, we use DRMAA as an interface for submitting tasks from G-Hadoop to the Torque Resource Manager.

2.4 Quality of Service (QoS)

Quality of Service (QoS) is a set metrics used to evaluate the overall performance of the datacenter Cloud , given the datacenter Cloud scheduling solution. Each metric evaluates the execution of a given job from one unique perspective. The performance is quantified by the fitness score between 0 and 1. A higher fitness score implies better execution quality. The overall performance of the datacenter Cloud on a specific job is determined by the summation of all fitness scores associated with the job. An effective Cloud computing scheduler optimizes the scheduling solution so that all QoS requirements are satisfied for each job. Our algorithm optimizes the scheduling using the following three QoS metrics.

- Timeliness. This metric defines the severity of missing the deadline of a job. The fitness score when missing the deadline is determined by the priority of the job. For example, for a job with a hard deadline, missing it would generate the fitness score of 0. For a job with no deadline, the fitness score is inversely proportional to the execution time.
- Reliability. Due to the autonomous nature of the datacenter Clouds, each Cloud datacenter has its own policy on its availability in the Cloud computing. In other words, some Cloud datacenters offer the computational power only in the idle state. Others offer all of the remaining resources even when internal tasks are under execution. The reliability of the Cloud datacenter is proportional to its availability. In other words, the Cloud datacenter offering stable computational power receives higher fitness score on reliability than the one disconnecting from the Cloud frequently.
- Security. Since there is no centralized administration over the Cloud, not every machine connected onto the Cloud is trustworthy. It is difficult to prevent malicious participants from compromising the Cloud by providing malfunctioning machines. The malfunctioning machines generate erroneous results and thus jeopardize the integrity of the datacenter Cloud .

2.5 QoS-aware Workload scheduling in datacenter Clouds

The traditional problem of workload scheduling for Cloud computing has been extensively studied. Since the problem is NP-Hard [27], many meta-heuristic algorithms have been proposed to query the optimal solution.

Classical resource management systems were designed for batch scheduling systems that rely on gang-scheduling model [54], which can allocate multiple resource types. The scheduling policies were dependent on job queues and priorities with the goal of keeping all resources busy rather

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than focusing on optimizing application level QoS. In the gang-scheduling model, jobs are queued and based on their priority they are assigned to cluster resources.

Datacenter management systems such as Amazon EC2, Microsoft Azure, and Eucalyptus, application administrators specify their resource requirements in terms of hardware (e.g. CPU type, CPU speed, number of cores, etc.) and software resource (virtualization format, operating system, etc.) configurations while ignoring specific QoS metrics such as response time, reliability, or security. Other systems such as YARN [55] , Apache Hadoop and Quincy [56] use a system centric fairness (e.g. CPU share or memory share) policy to map jobs to resources. These systems do not allow application administrator to specify and enforce application level QoS metrics and policies. Mesos [57] uses two-level scheduling to manage resources of a cluster that can be hosted within a public or private datacenter. Mesos does not support any scheduling policy, but is a framework that can support multiple policies. The approach proposed in this paper can be implemented as a scheduling policy in Mesos for ensuring application level QoS metrics.

A Chemical Reaction Optimization (CRO) is proposed [27]. The algorithm mimics the chemical reactions during which the potential energy of molecules is minimized. Each candidate scheduling solution is modeled as a molecule with certain potential energy. The potential energy is modeled as the overall quality of the scheduling solution. During each iteration, molecules are selected to perform chemical reactions with each other, generating new molecules with potentially lower potential energy, or solutions with better quality. The solution quality is evaluated by timeliness and reliability of the datacenter Cloud . The simulation results show that CRO based algorithm can generate better solutions than other meta-heuristics like Genetic Algorithm (GA) and Simulated Annealing (SA).

The other meta-heuristic Cloud computing scheduler combines Particle Swarm Optimization (PSO) and Gravitational Emulation Local Search (GELS) [28]. The fitness function of the PSO is inversely proportional to the completion time of the last executed job and the number of jobs missing their deadlines. During each iteration, every candidate scheduling solution is updated towards better fitness values. GELS is used to improve the candidate pool to avoid local optima. The experimental results show that it significantly reduces the completion time of the last job compared to other heuristics.

The common weakness of the previous works is that their scheduling solutions are optimized in terms of only one metric, timeliness. Since other metrics like security and reliability are not used in the optimization, those algorithms may suffer severely from sub-optimality. In this work, the comprehensive model of Quality of Service (QoS) is proposed for evaluating the performance of the datacenter Cloud . The QoS model generates more practical evaluation from various perspectives including timeliness, reliability and security.

3 MODELS

In this section, the system model, the workload model and the QoS model are first introduced. Based on them, the cloud datacenter model is established.

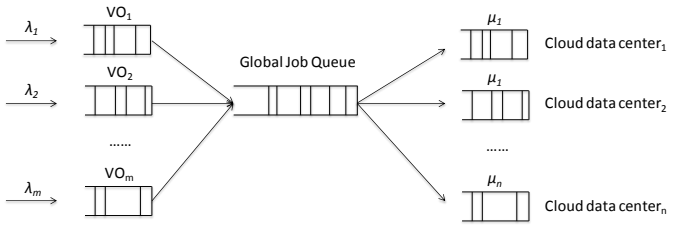

Fig. 2: System model

3.1 System model for Datacenter Cloud computing

The whole system is modeled as a M/M/1 system. The following assumptions about the system model.

- the incoming jobs are modeled as exponential distribution,
- the service rate of Cloud datacenters are exponential distributed,
- each Cloud datacenter is modeled as one server,
- the Cloud datacenter's service discipline is non-preemptive and First Come First Serve (FCFS).

3.2 Workload model

It is assumed that there are m Virtual Organizations (VOs) that share the datacenter Cloud system defined above. Each VO is modeled as a VO Job Queue (VOJQ). All jobs from VOJQs are submitted a Global Job Queue (GJQ). We define that:

- λ^i is the arrival rate of the VO_i, $1 \leq i \leq m$
- λ_j^i is the arrival rate of jobs of VO_i on the Cloud datacenter $Site_j$, $1 \leq i \leq m$, $1 \leq j \leq n$
- λ_j is the arrival rate of jobs from all VOs on the Cloud datacenter $Site_j$, $1 \leq j \leq n$, $\lambda_j = \sum_{i=1}^{m} \lambda_j^i$
- λ is the arrival rate of all VOs, $\lambda = \sum_{i=1}^{m} \lambda^i$

The job distribution possibility matrix is defined as follows:

$$P = [p_{ij}] = \begin{bmatrix} p_{11} & p_{12} & p_{1n} \\ p_{21} & p_{22} & p_{2n} \\ \vdots & \vdots & \vdots \\ p_{m1} & p_{m2} & p_{mn} \end{bmatrix} \quad (1)$$

p_{ij} is the possibility that a job from VO_i is scheduled to the Cloud datacenter $Site_j$, $1 \leq i \leq m, 1 \leq j \leq n$.

Therefore, the following is obtained.

$$\lambda_j^i = p_{ij} \times \lambda^i \quad (2)$$

$$\lambda_j = \sum_{i=1}^{m} (p_{ij} \times \lambda^i) \quad (3)$$

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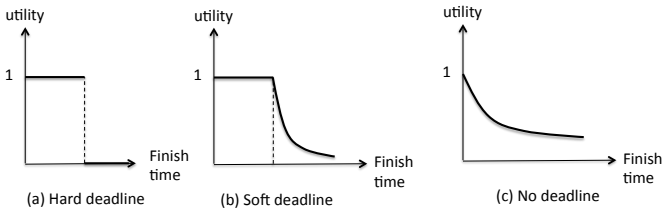

Fig. 3: Sample utility function: timeliness

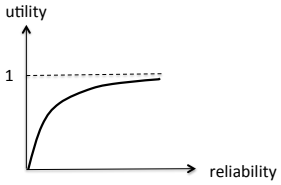

Fig. 4: Sample utility function: reliability

3.3 QoS model

Assume there are totally s QoS requirements, $Q = [Q_1, Q_2, \ldots, Q_s]$. Examples of QoS include availability, timeliness, security, and reliability, Therefore the QoS requirement matrix for all VOs is as follows:

$$Q = [q_{ik}] = \begin{bmatrix} q_{11} & q_{12} & q_{1s} \\ q_{21} & q_{22} & q_{2s} \\ \vdots & \vdots & \vdots \\ q_{m1} & q_{m2} & q_{ms} \end{bmatrix} \quad (4)$$

where, q_{ik} is a requirement of tasks in VO_i for QoS Q_k, $1 \leq i \leq m$, $1 \leq k \leq s$.

As QoS definition is associated a utility function [58], [59], which defines the benefit received by a VO. The utility function associated with q_{ik} is defined as:

$$q_{ik} : q_{ik} \rightarrow \mathbf{R} \quad (5)$$

where, $1 \leq i \leq m$, $1 \leq k \leq s$ and $\mathbf{R}$ is the set of positive real numbers. Examples of normalized utility functions are shown in Figure 3, 4 and 5. Figure 3 shows a task is associated with (a) a hard deadline, (b) a soft deadline and (c) no deadline. A task with the reliability QoS requirement is shown in Figure 4 and a task with the security QoS requirement is shown in Figure 5.

The above models are limited to express an individual QoS for a task, it is thus required to develop a further model that can express multiple QoS requirements for different VOs. The concept of weighted QoS achievement is proposed to denote the concept of QoS interests obtained for a job

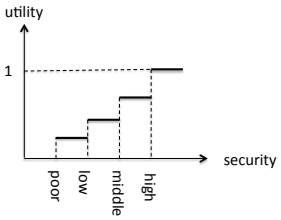

Fig. 5: Sample utility function: security

distribution of a VO on a Cloud datacenter. The weighted QoS achievement for VO_i is defined as following:

$$a_i = \sum_{k=1}^{s} w_{ik}(q_{ik}^{req} - q_{ik}^{get}) \quad (6)$$

where,

- $1 \leq i \leq m, 1 \leq k \leq s$
- w_{ik} denotes the weight of QoS Q_k for VO_i, $\sum_{k=1}^{s} w_{ik} = 1$
- q_{ik}^{get} denotes the QoS Q_k allocation for VO_i, and
- q_{ik}^{req} denotes the VO_i's requirement for QoS Q_k.

Given the job distribution possibility matrix defined in Equation 1, the q_{ik}^{get} can be calculated as follows:

$$q_{ik}^{get} = \sum_{j=1}^{n}(p_{ij} \times \tilde{q}_{jk}) \quad (7)$$

where $\tilde{q}_{jk}$ is the QoS allocation of Q_k from Site S_j.

The overall QoS achievement for all VOs is defined as follows:

$$A(P) = \sum_{i=1}^{m} a_i \quad (8)$$

Where is P is a job distribution possibility matrix and defined in Equation 1. It is thus an objective for a job distribution to maximize the overall QoS achievement for all VOs from a system perspective.

3.4 Cloud datacenter model

The service rate of a Cloud datacenter site is modeled as follows:

- μ_j is the service rate of the Cloud datacenter $Site_j$, $1 \leq j \leq n$,
- μ_j^i is the service rate of jobs of VO_i on the Cloud datacenter $Site_j$, $1 \leq j \leq n, 1 \leq i \leq m$.

The following part of this section models the unreliability of Cloud datacenters. The unreliable production Cloud datacenter is modeled with a set of successive periods of "up" and "down" as follows.

- η_j: the rate of up state of Cloud datacenter $Site_j$, and
- θ_j: the rate of Cloud datacenter down state of Cloud datacenter $Site_j$.

We define

- $E(S_j^i)$ is the sojourn time of a job from VO_i at a Cloud datacenter $Site_j$ and
- $E(L_j^i)$ is the queue length when the job from VO_i arrives at Cloud datacenter $Site_j$.

$E(S_j^i)$ is derived as follows. In case the job meets a reliable Cloud datacenter, the job's sojourn time is:

$$E_1 = \frac{E(L_j^i) + 1}{\mu_j^i} \quad (9)$$

However, the Cloud datacenter is unreliable, there exist extra waiting time due to down states of a Cloud datacenter.

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The mean number of down states experienced by the job is equal to $\eta_j \times \frac{E(L_j^i)+1}{\mu_j^i}$, and the mean duration of each down state is $\frac{1}{\theta_j}$. There for the extra waiting time due to down states of a Cloud datacenter is

$$E_2 = \eta_j \times \frac{E(L_j^i)+1}{\mu_j^i} \times \frac{1}{\theta_j} \tag{10}$$

Furthermore, the Cloud datacenter $Site_j$ is already down when the job comes, then there is another extra delay:

$$E_3 = \frac{1}{\theta_j} \times \frac{\eta_j}{\theta_j + \eta_j} \tag{11}$$

Therefore the sojourn time of a job from the i^{th} VO VO_i at a Cloud datacenter $Site_j$ is as follows:

$$\begin{aligned} E(S_j^i) &= E_1 + E_2 + E_3 \\ &= \frac{E(L_j^i)+1}{\mu_j} + \eta_j \times \frac{E(L_j^i)+1}{\mu_j} \times \frac{1}{\theta_j} \\ &\quad + \frac{1}{\theta_j} \times \frac{\eta_j}{\theta_j + \eta_j} \end{aligned} \tag{12}$$

Then, with Little's law:

$$E(L_j^i) = \lambda_j^i \times E(S_j^i) \tag{13}$$

the following is obtained:

$$E(S_j^i) = \frac{\frac{1}{\mu_j^i \times \rho_U} + \frac{\rho_D}{\theta_j}}{1 - \frac{\lambda_j^i}{\mu_j^i \times \rho_U}} \tag{14}$$

where,

- $\rho_D = \frac{\eta_j}{\eta_j + \theta_j}$: the fraction of down state of a Cloud datacenter.
- $\rho_U = \frac{\theta_j}{\eta_j + \theta_j}$: the fraction of up state of a Cloud datacenter.

Consequently,

$$E(S^i) = \sum_{j=1}^{n} (p_{ij} \times E(S_j^i)) \tag{15}$$

Finally, the mean sojourn time for all VOs is as follows:

$$E(S) = \sum_{i=1}^{m} (\frac{\lambda_i}{\lambda} \times E(S^i)) \tag{16}$$

It is thus an objective for a job distribution to minimize the mean sojourn time for all VOs from a system perspective.

4 Scheduling Algorithms

4.1 Research issue definition

It is assumed that there is a global scheduler that schedules workloads in the Cloud Job Queue to multiple Cloud datacenters (see also Figure 2). A global scheduler distributed incoming workloads from various VOs to multiple Cloud datacenters with the following objectives:

- minimize the mean sojourn time for all VOs $E(S)$, and
- minimize the QoS advantage $A(P)$.

Formally based on the job model and Cloud system model, the schedule function is defined as follows:

$$f : (VO, Site) \rightarrow P, \qquad f \in \mathbf{F} \tag{17}$$

where F is a set of all feasible schedule functions.

The research issue is defined as follows:

To find a schedule function $f \in \mathbf{F}$, which gives the $\min E(S)$ and $\min A(P)$.

4.2 Cross Entropy Theoretical Foundations

Cross entropy optimization, originally proposed in [60], is a stochastic optimization technique based on the theory of importance sampling. It casts a deterministic optimization problem into a stochastic optimization problem which can be solved to approximate the optimal solutions. This powerful optimization framework has been successfully applied to various different combinatorial optimizations problems such as those in [61], [62], [63], [64], [65], [66], [67]. For completeness, some details of this technique provided in [60], [68] are elaborated as follows.

To minimize a function $\min_{x \in \mathcal{D}} f(x)$ with variables x defined in the solution space $\mathcal{D}$, cross entropy firsts converts it into a stochastic optimization problem. That is, it uses a set of probability density functions (PDF) $g(x, p)$ defined in the space $\mathcal{D}$ to model the possible distributions on the solutions of the minimization problem. Given a set of random samples $X = \{X_1, X_2, \ldots, X_n\}$ generated according to $g(x, p)$, one can define $\delta(a)$ as

$$\delta(a) = P[f(X) \leq a], \tag{18}$$

where a is a parameter. Define an indicator function $I(\cdot)$ such that $f(x) \leq a$ if and only if $I_{f(x) \leq a} = 1$. Therefore, $P[f(X) \leq a] = E[I_{f(X) \leq a}]$ where E denotes the expectation. It is clear that if one can computes the largest a which makes $\delta(a)$ approach zero, this a gives a near optimal solution for the minimization problem $\min_{x \in \mathcal{D}} f(x)$. This is the basic idea of the conversion of a deterministic minimization problem to a stochastic minimization problem.

However, when $\delta(a)$ approaches zero, it is difficult to evaluate its value. If one uses the straightforward Monte Carlo simulations based technique, a large number of samples will be needed which is computationally expensive. That is, one can generate a set of samples according to $g(x, u)$ and an unbiased estimator is

$$\delta(a) = \frac{1}{n} \sum_{i=1}^{n} I_{f(X_i) \leq a} \tag{19}$$

As the solution approaches the optimal solution, $\delta(a)$ will approach zero, which means that a large number of samples are needed. In other words, $f(X) \leq a$ becomes a *rare event*. This is why cross entropy technique uses the importance sampling to tackle this technical difficulty.

In contrast to using $g(x, p)$, the importance sampling in the cross entropy technique uses a variant probability density function $k(x, p)$ also defined on $\mathcal{D}$. $\delta(a)$ can then be approximated by

$$\widehat{\delta}(a) = \frac{1}{n} \sum_{i=1}^{n} I_{f(X_i) \leq a} \frac{g(X_i)}{k(X_i)} \tag{20}$$

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Suppose that one can compute $k^*(x)$ such that $k^*(x) = \frac{I_{f(X_i)\leq a} g(x,u)}{\delta(a)}$. One has

$$\widehat{\delta}(a) = \frac{1}{n}\sum_{i=1}^{n} I_{f(X_i)\leq a} \frac{g(X_i)}{k^*(X_i)} = \delta(a) \quad (21)$$

The technical difficulty is that k^* cannot be computed explicitly. Therefore, the cross entropy technique uses a PDF which well approximates $k^*(x)$. This PDF has the property that it minimizes the so-called cross entropy between the two PDFs $k(x)$ and $g(x,v)$, which is

$$d(k,g) = E_g \ln \frac{k(X)}{g(X)} = \int k(x)\ln k(x)dx - \int k(x)\ln g(x)dx \quad (22)$$

Plugging this into the original functions, one has

$$argmax_v \int k^*(x)\ln g(x,v)dx \quad (23)$$

which is

$$argmax_v E_u I_{f(X)\leq a} \ln g(X,v) \quad (24)$$

The cross entropy technique uses importance sampling technique again with the new parameter w such that

$$argmax_v E_u I_{f(X)\leq a} \frac{f(x,u)}{f(x,w)} \ln g(X,v) \quad (25)$$

Subsequently, the solution to the original minimization problem can be written as

$$\widehat{v}^* = argmax_v \frac{1}{n}\sum_{i=1}^{n} I_{f(X_i)\leq a} \frac{f(X_i,u)}{f(X_i,w)} \ln g(X_i,v) \quad (26)$$

where the samples X are generated using $g(x,w)$. Refer to [60], [68] for the further details.

4.3 Cross Entropy Based Scheduling Algorithm

This work proposes a Cross Entropy based Scheduling Scheme (CESS) Algorithm to optimize the QoS and the waiting time. The CESS algorithm is iteratively proceeded to the solution by updating the probability density function (PDF) throughout the whole optimization procedure. This PDF is used to depict the candidate job assignments and employed to generate samples during each iteration. In this work, the Gaussian distribution is employed as the PDF function to solve the scheduling problem. Note that, the sample here denotes a scenario of the job assignment. On the other hand, the PDF are updated by elite samples in each iteration, where elite samples are job assignments which are high quality solutions in terms of the QoS and the waiting time.

Figure 6 shows the details of the CESS algorithm and Figure 7 shows an example of one iteration of the algorithm. The proposed algorithm first initialize the PDF array for all Cloud datacenters. Each Cloud datacenter is associated with a PDF over the its selection index (SI), an variable indicating the preference of our selection. A higher SI implies higher probability for the corresponding Cloud datacenter to be selected. If it is not the first iteration, the PDF array is inherited from the last iteration. Otherwise, each PDF is initialized with the same mean and variance, as indicated in Figure 7.

Subsequently, n samples are generated according to the PDF array. For each sample, a selection score is generated for each Cloud datacenter according to the corresponding PDF. The Cloud datacenter with the largest selection score

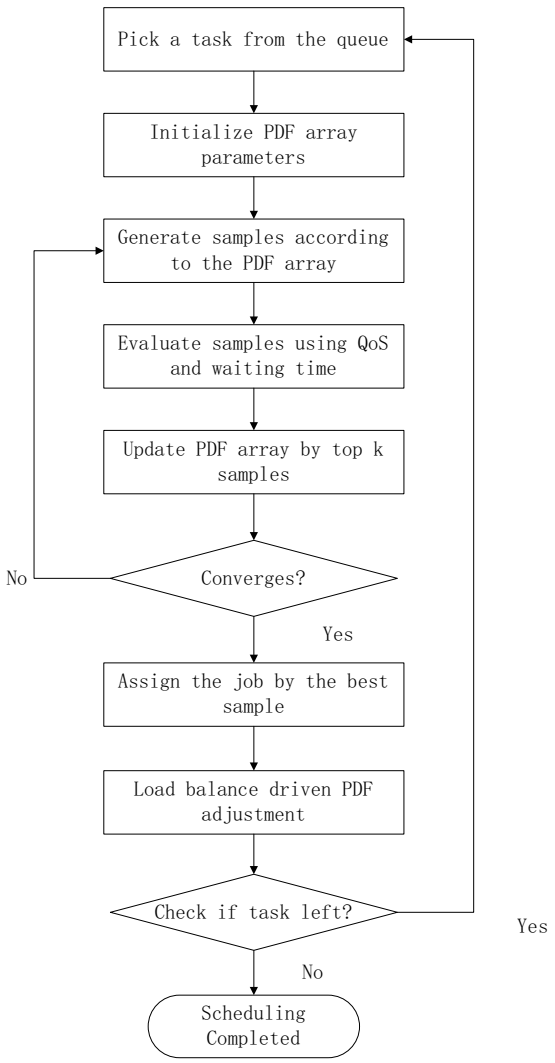

Fig. 6: Cross Entropy Based Scheduling Algorithm Flow

is the one selected for that sample. For example, for sample 1 in Figure 7, Cloud datacenter 1 has the largest score of 0.6, so it is selected in that sample. Similarly, Cloud datacenter 2 is selected in sample 2. For the case in which several Cloud datacenters share the same largest selection scores, the one with the largest mean on its PDF is selected. The reason is that, statistically, the one with the largest mean on the PDF performs the best.

After n samples are generated, each one is evaluated by QoS and sojourn time. k samples with the best QoS and Sojourn time form the set of elite samples. For the Cloud datacenter selected for elite samples, the mean is increased for the corresponding PDF. For each PDF, the variance is decreased. For example, as shown in Figure 7, suppose sample 1 and sample 2 are elite samples. Since Cloud datacenter 1 and 2 are the selected for the two samples, the PDFs are updated with larger mean. In this way, the Cloud datacenters with better QoS and sojourn time become more likely to be generated while the algorithm approaches convergence. If the algorithm goes through λ iterations or all samples selects the same Cloud datacenter, the convergence

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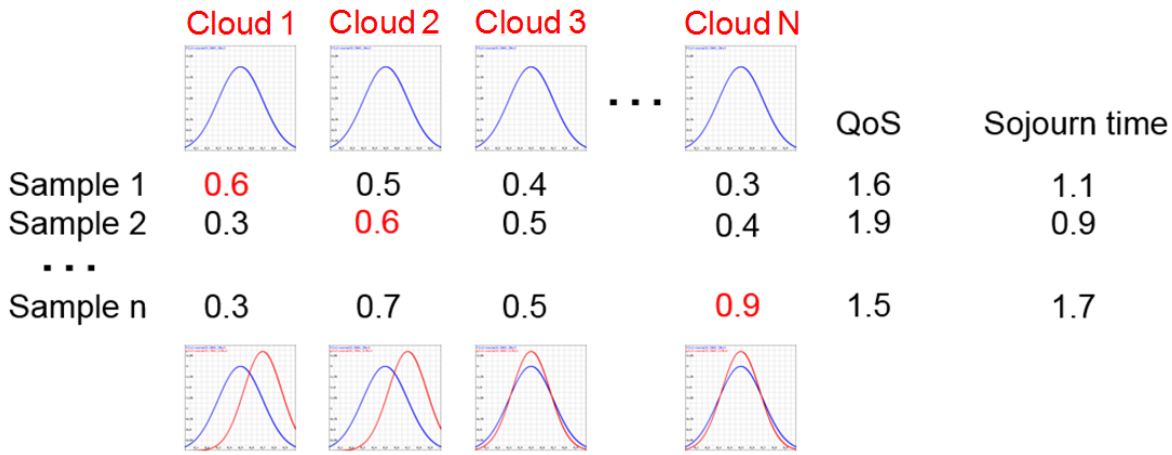

Fig. 7: Example of one iteration of CESS algorithm. The updated PDF for each is indicated by red curves.

criterion is met. After convergence, the job is assigned to the Cloud datacenter for the sample with the best QoS and sojourn time.

Straight forward implementation of the CESS algorithm would suffer from Cloud datacenter overloading issue. The reason is that the algorithm tends to assign every job to the Cloud datacenter with the best QoS. Consequently, the best Cloud datacenter becomes overloaded. To alleviate the issue, the load-balance driven PDF adjustment is proposed. That is, the mean value of the PDF of the Cloud datacenters selected is intentionally increased. As a result, the chance for a Cloud datacenter to be repeated selected is decreased and the loads are more evenly distributed over the Cloud datacenters.

5 Experimental Results

The proposed cross entropy based QoS-aware Workload scheduling with the Stochastic Modeling technique is implemented in C++ and tested on a machine with 2.8 GHz Intel® Core™ i5 CPU, 4 GB memory and 64 bit operating system. Due to inaccessibility to real world distributed datacenters, we construct a set of 500 synthetic test cases with up to 1000 VOs and 50 Cloud datacenters.

To demonstrate the superiority of our Cross Entropy based Scheduling Scheme (CESS) algorithm, we compare it with the baseline greedy algorithm. The baseline algorithm always greedily assigns the incoming jobs to the Cloud datacenter with the best Quality of Service (QoS) and least sojourn time. Note that, the QoS value includes the reliability and security values with weighted factors. The solutions to both algorithms on each test case is evaluated using the following metrics.

- Accumulative sojourn time of all jobs. Since our target is to minimize the average queuing time for all jobs, the scheduling quality is inversely proportional to this metric.
- Accumulative QoS fitness score of all jobs provided by all Cloud datacenters. Each QoS fitness score is the weighted sum of timeliness score, reliability score and security score. A higher QoS fitness score suggests faster execution time, higher reliability and better security. Apparently, the scheduling solution quality is proportional to this metric.

The comparison between the baseline greedy algorithm and our CESS algorithm is shown in Table 1. We have the following observations.

- In contrast to the baseline algorithm, our CESS algorithm generates better accumulative QoS on every test case. Statistically, the QoS is improved by 56.1% on average from the baseline algorithm. The reason is that our algorithm optimizes the scheduling of every job in terms of the QoS and the sojourn time.
- Comparing with the greedy algorithm, the proposed CESS algorithm can save up to 25.4% waiting time. On average, the waiting time is saved by 9.2%. The greedy algorithm tends to assign all jobs to the site with the best QoS. Apparently it overloads the Cloud datacenter, resulting in larger sojourn time. In contrast, the PDF performance-tuning in our algorithm mitigates the overburden of Cloud datacenters. It limits the probability that a particular Cloud datacenter is frequently selected, so that jobs are evenly distributed over the Cloud datacenters. Consequently, the accumulative sojourn time is decreased.
- The proposed algorithm are performed very efficiently. The results over all test cases can be within 864.55 seconds on average. Apparently, the runtime scales only linearly with test cases of different sizes.
- Although the waiting time of the greedy algorithm are quite close to the proposed algorithm, the QoS of the proposed algorithm dominates the greedy one.

To assess the performance of our algorithm in real world, we evaluate our CESS algorithm with different job arrival rate and Cloud service rate. The resulting sojourn time and QoS are shown in Figure 8. We have the following observations.

- Within the same period of time, the accumulative QoS and waiting time is proportional to the job arrival rate. As the job arrival rate increases, more jobs are handled by the Cloud datacenters. Since each job, handled by a Cloud datacenter, produces

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Fig. 8: QoS and waiting comparison with different job arrival rate and Cloud service rate

TABLE 1: Comparisions of QoS, waiting time and runtime among the greedy algorithm and the proposed CESS algorithm with varying sizes when tasks are assigned to a cluster system.

Testcase Size	Number of Clouds	Greedy Algorithm			CESS Algorithm			Improvement	
		QoS	Waiting Time	Runtime(ms)	QoS	Waiting Time	Runtime(s)	QoS	Waiting Time
50-100	10	47995.7	6748.6	1.38	64071.5	5037.7	30.11	33.5%	25.4%
101-200	20	125640.2	15984.0	4.32	180122.1	14214.51	178.37	43.4%	11.1%
201-400	30	252917.5	55384.2	9.10	378107.5	52555.5	567.75	49.5%	5.1%
401-600	40	409185.2	119858.9	14.86	628853.1	115267.9	1195.19	53.7%	3.8%
601-1000	50	630207.1	256373.7	25.81	983728.9	255296.8	2351.33	56.1%	0.0%
Average	-	293189.2	90869.88	11.09	446976.64	88474.49	864.55	47.2%	9.08%

a QoS value, the accumulative QoS increases. Larger waiting time can be explained by the gird site overloading effect. With the same Cloud service rate, increasing arrival rate requires Cloud datacenters to handle more jobs. Consequently, the accumulative waiting time increases.

- For the same amount of jobs with the same job arrival rate, both the accumulative QoS and the waiting time can be improved by increasing the Cloud service rate. Apparently the waiting time is inversely proportional to Cloud service rate. The PDF performance-tuning in our algorithm contributes to the improved QoS. With higher Cloud service rate, the Cloud datacenter overloading issue is mitigated. Since each Cloud datacenter is able to handle more jobs, the PDF performance-tuning intelligently assigns more jobs to sites with better QoS. As a result, the accumulative QoS is improved.
- By increasing both the job arrival rate and the Cloud service rate, both QoS and waiting time increase. Again, increment in accumulative QoS is due to the additional jobs, each contributing a QoS value to the accumulative QoS. In contrast to the case with higher job arrival rate and the same service rate, the waiting time does not increase dramatically with the job arrival rate. It suggests that the severity of Cloud datacenter overloading is significantly alleviated. Therefore, our algorithm has the capacity to be deployed in the real world, given steady service rate/job arrival rate ratio.

6 Conclusion

Cloud computing, which delivers computing as a service, has emerged as a promising computing paradigm which offers vast computing power and flexibility. However, it faces many challenges such as system modeling with variations and optimization scheduling issues. This work proposes a stochastic modeling of workload scheduling for the cloud computing environment considering timeliness, security and reliability. A cross entropy based QoS-aware workload scheduling technique is developed to compute scheduling solutions optimizing the QoS metric. Our experiments on 500 testcases demonstrate that the proposed approach significantly outperforms the greedy algorithm with up to 56.1% QoS improvement with largest size of testcases and 25.4% waiting time improvement with the testcases which has the size of $50 - 100$.

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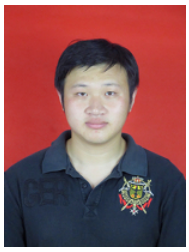

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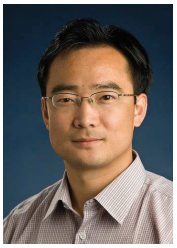

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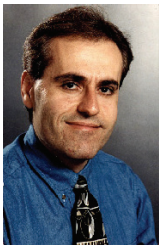

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