CTaG: An Innovative Approach for Optimizing Recovery Time in Cloud Environment

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Abstract

Traditional infrastructure has been superseded by cloud computing, due to its cost-effective and ubiquitous computing model. Cloud computing not only brings multitude of opportunities, but it also bears some challenges. One of the key challenges it faces is recovery of computing nodes, when an Information Technology (IT) failure occurs. Since cloud computing mainly depends upon its nodes, physical servers, that makes it very crucial to recover a failed node in time and seamlessly, so that the customer gets an expected level of service. Work has already been done in this regard, but it has still proved to be trivial. In this study, we present a Cost-Time aware Genetic scheduling algorithm, referred to as CTaG, not only to globally optimize the performance of the cloud system, but also perform recovery of failed nodes efficiently. While modeling our work, we have particularly taken into account the factors of network bandwidth and customer’s monetary cost. We have implemented our algorithm and justify it through extensive simulations and comparison with similar existing studies. The results show performance gain of our work over the others, in some particular scenarios.

Keywords: Cloud computing, task scheduling, big data, recovery time, offloading

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1. Introduction

Cloud computing (CC) has emerged as a promising as well as inevitable technology [9], deemed as an ideal solution to handle the requirements of today’s increasing demands, more specifically, in terms of availability, total cost of ownership (TCO), and time to value (TTV) [20, 21]. Number of enterprises, specially large-scale businesses, have been adopting CC, resulting in popularity of cloud-based services. For highly computationally complex business processes, CC is becoming a necessity.

To achieve high performance, reliability, and availability of cloud services, thousands of servers coordinate with each other for efficient task scheduling and in the end, user satisfaction [4]. While achieving this, at times, computing nodes in a datacenter may fail, causing degradation of performance. Although, it is not very common for a server to face such situation, but across all devices in the datacenter, the effect can be very diverse [5]. Failure of nodes can not only adversely affect the performance, but also, reliability of services being provided [2]. Financial damage may be up to millions of dollars, if the system is not recovered in time [1]. On the other hand, customers may lose their trust, resulting in huge financial loss for the service provider. Service providers would always like their customers to be loyal with them and this depends mainly upon the quality and integrity of services.

Other than the major facilities, like affordable cost, quick deployment, scalability, etc., cloud computing comes with, resiliency is considered to be a vital feature of it. It is very important to bring back the infrastructure into its original working state as soon as possible. Availability of the system and quick recovery from a failed state determines the level of trust of customers. That is why, in case of any failure, the system is ought to be brought back to normal seamlessly. In respect of recovery from failure, research activities have been focusing on different methodologies to minimize recovery time in high performance computing. Methodologies are mainly categorized into two: stochastic optimization [22, 23] and heuristic-based optimization [8, 10]. Heuristic approach solves the problem efficiently, but compromising on the performance. On the other hand, stochastic approach has a comparatively better performance, keeping in view the reliability of solution [6]. Both these approaches have their pros and cons, but overall, none of these approaches are preferable, since they do not take into account the network condition and monetary cost customers have to pay. In our work, we have tried our best to keep the advantages of both of these approaches and overcome their limitations. We present an efficient and cost-effective method, based on genetic algorithm, called CTaG, for task scheduling to globally optimize cloud-based system performance and reduce recovery time for physical server failures in cloud computing. Besides overall efficiency and reliability, we have considered network condition and monetary cost while designing our system. In designing our system, we foresee that the overall processing time of the cloud system can be significantly reduced and user experience and quality of service can be improved.

We have evaluated our methodology through extensive simulations to justify its efficiency and performance. Comparison with the existing approaches proves the edge our approach has over the others. Our approach minimized both recovery time of failed nodes and monetary cost of customers, with a lower overhead, as compared to other approaches. As a result, a better efficiency per cost (EC) ratio is achieved. We believe that our approach can be very useful for the discussed situations, especially for small and medium sized business models, working on cloud based services.
The organization of this paper is in such a way that section 2 discusses already done work in this regard. Section 3 presents motivating scenarios and importance of our approach. We present our methodology in section 4. Implementation and evaluation are presented in section 5. Section 6 concludes our paper.

2. Related Work

There is a survey of 584 individuals in U.S. organizations who have responsibility for data center operations. Among those organizations which experienced a loss of primary utility power, 91 percent reported unplanned outages [13]. Unplanned data center outages present a difficult and costly challenge for organizations. Therefore, to deliver better services to customers, cloud-based infrastructures are expected to come up with failure-tolerance and resiliency, which implies that those systems can be quickly recovered from failure because of the outages and restored to normal working state, especially for distributed systems. In those heterogeneous systems, scheduling algorithms play a key role in obtaining high performance.

There have been numerous studies which attempt to solve task scheduling problems, where the sequence of the tasks (workflow) is popularly presented by a directed acyclic graph (DAG), as shown in Fig. 4. In [7], authors propose task scheduling approaches for assigning processors to task graph templates prepared in advance. The limitation of these methods is that they do not consider the network contention. They assume that the network has a perfect communication, and there is no limited bandwidth. Sinnen et al. [8] present an efficient task scheduling method based on network contention. This proposal has two steps: firstly, each task is set a priority based on the upward value of this task in the workflow; secondly, choose the most appropriate processor that minimizes the completion time of this priority based task. Anyhow, the method does not look attentively at monetary cost paid by cloud service customers (CSCs), for use of the cloud resources.

In heterogeneous CC environment, despite numerous efforts, task scheduling remains one of the most challenging problems [6]. Good performance of workflow and satisfaction of a budget constraint are typical criteria for multitask scheduling. Authors in [28] introduce a cost-efficient approach to select the most appropriate system (private or public cloud) to execute the workflow. Selection also depends on the possibility of meeting the deadline of each workflow as well as the cost savings. L.Zeng et al. in [3] propose budget conscious scheduling Comparative Advantage (CA) function to satisfy the strict budget constraint. In its first phase, each of tasks is assigned to the best VM whose CA1 value is maximum to get a worthy tradeoff between cost saving and efficiency. In the second phase, budget constraint is used in the CA2 function to evaluate the improvement of task reassignment to another VM on cost and performance. Notwithstanding CA is hard to be applied to the large-scale workflows. In the meantime, J. Li et al. in [11] present a scheduling algorithm CCSH to schedule the application of large graph processing with considering both cost and schedule length. The input cost-conscious factor of this method is the cloud cost and used as a weight to calculate the earliest finish time EFT of each task. However, global optimality and tradeoff between cost and schedule length are not properly addressed in these approaches.

Recently, some GAs have been developed for solving the global optimal problem in task scheduling. The authors in [22] propose approaches using genetic processes to find multiple solutions faster and ensure global optimal usage of the processing system. Sachi et al. [23] develop a method based on genetic algorithm (GA) to find an optimal scheduling, which shows to be efficient to discover optimal solutions more than Heterogeneous Earliest Finish Time (HEFT) with same length of problem size, focusing on the quality of solution and effect
of mutation probability on the performance of GA. Mohammad A. et al. [26] propose a GA based method which not only considers the deadline time in sorting the tasks in the first population, but also includes the maximum computational time of individuals in the population to define the priority level of these tasks. Hadis H. et al. [25] exhibit a node duplication genetic algorithm based technique to avoid some unnecessarily replicated node without any negative affect on its schedule length for minimizing inter processor traffic communication. Yujia et al. [27] show a new scheduling algorithm according to a fitness adaptive algorithm-job spanning time adaptive genetic algorithm, so as to enhance the overall performance of the cloud computing environment. Nonetheless, in these proposals, monetary cost and failure of computing devices are not considered.

Zhang et al. in [19], and Y.Gu et al. in [14] introduce a solution to recover from failure according to check-pointing in stream processing system. As such, when the system has failure, it finds the closest ancestor node which is not impacted by failure to resume the results saved in that node. The authors in [10] come up with a scheme to reduce the recovery time in case of failure, but they do not contemplate the cost paid by users. Similar to our approach, Huynh T.T.B in [24] proposes a genetic based method that minimizes the processing against a failure in a network system. But monetary cost is not considered in this solution.

For ease of understanding, we present an overview of common scheduling approaches along with ours in Table 1.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Target System</th>
<th>Minimum Schedule Length</th>
<th>Minimum Cost</th>
<th>Trade off</th>
<th>Minimum Recovery Time</th>
<th>Global Optimality</th>
</tr>
</thead>
<tbody>
<tr>
<td>H. Topcuoglu et al. [16]</td>
<td>Heterogeneous</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Oliver Sinnen et al. [8]</td>
<td>Cloud</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Gonzalo et al. [15]</td>
<td>Cloud</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Louis C. et al. [17]</td>
<td>Heterogeneous</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>L.Zeng et al. [3]</td>
<td>Cloud</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Ruben et al. [28]</td>
<td>Cloud</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>J. Li et al. [11]</td>
<td>Heterogeneous</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Shohei G. et al. [10]</td>
<td>Multicore processor</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Zhang et al. [19]</td>
<td>Stream processing</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Tashniba K. et al. [22]</td>
<td>Multicore processor</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Sachi et al. [23]</td>
<td>Heterogeneous</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Hadis H. et al. [25]</td>
<td>Multicore processor</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Mohammad A. et al. [26]</td>
<td>Multicore processor</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Yujia et al. [27]</td>
<td>Cloud</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Huynh T.T.B [24]</td>
<td>Homogeneous</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Our approach</td>
<td>Cloud</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>
As shown in Table 1, a desirable scheduling approach should consider all of the four factors including globally optimal execution time, network contention, cost of using cloud services and recovery time in the case of physical failure of servers. That can satisfy QoS as well as increase reliability and the reputation of the cloud provider. In this paper, we aim to provide a scheduling scheme which takes these factors into account and develop an algorithm to reduce the recovery time in the case of failure of a physical server in a data center. The main contribution of this work is the development of a genetic algorithm to determine the global optimal schedule.

3. Motivation Scenario

In this section, we discuss the importance and applicability of our work, by presenting relevant scenario. Fig. 1 illustrates cloud datacenter, having several physical servers (PSs), represented by bounded rectangles. Each of which may not have enough capacity to host all processors (rectangles), functioning as virtual machines (VMs), to fulfill user requirements in solving some computationally intensive tasks. These processors can communicate with each other via a network interface (gray circle). In one physical server, even if there is enough capacity, it is generally not recommended to have all the processors hosted in the same PS in order to avoid complete service unavailability in the case of power outage. Therefore, it is suggested, that tasks should be divided into smaller subtasks which are executed by processors (or VMs), located on different physical servers at the cloud provider side. Each of those processors can execute tasks independently.

![Fig. 1. A typical data center](image1)

![Fig. 2. An example of existing task scheduling (a) and recovery solution (b)](image2)
One network interface is shared among the scheduled processors. Due to the high stability of the network among processors in the same local PS compared with the Internet, the average data transfer rate of internal communication is always higher than that of external one. In this regard, existing schedulers try to utilize this high speed link, resulting in many dependent tasks being assigned to processors hosted in the same PS. When a failure occurs, dependent tasks tend to be destroyed at a time, requiring a more time consuming process for recovery.

In Fig. 2a an example is illustrated, regarding task scheduling created by an existing approach which does not consider the possibility of the system failure. In this scheduler, task \( v_1 \), \( v_2 \), and \( v_3 \) are assigned to processors \( P_1 \) and \( P_2 \) that are located in the same PS in order to utilize the high speed communication between processors. After task \( v_1 \) and \( v_2 \) are executed in parallel, task \( v_3 \) can be processed on processor \( P_1 \). However, if the PS on which \( P_1 \) and \( P_2 \) reside fails while task \( v_3 \) is being executed, the results of all task nodes, are lost. If we want to recover the results, all the tasks \( v_1 \), \( v_2 \), and \( v_3 \) have to be performed again on another physical server. This may double the execution time (Fig. 2b).

Let us now discuss another situation where all tasks in the critical path are assigned to processors in the same physical server. In this regard, the worst case scenario is that a failure of a physical server occurs during the time when the last tasks are being executed and the entire set of tasks have to be executed again. Here, the critical path refers to the longest execution path between the initial task (entry task) and the final task (end task) of the workflow, and this greatly influences the completion time of the DAG [10]. A one-hour delay in one of these tasks may immediately imply a one-hour delay on the workflow. Therefore, it is recommended that the tasks in the critical path should be distributed among processors residing in different PSs in order to improve the recovery time of a failure. As a trade-off, however, the communication overhead increases if no failure happens due to the extra communication between processors (Fig. 3a).

In case, if a failure occurs in our proposed system, only the result of task \( v_3 \) is lost since the results of task \( v_1 \) and \( v_2 \) are still stored in the other PS. Hence, only task \( v_3 \) needs executing again on the non-failure PS. This can reduce recovery time (Fig. 3b). However, it will become counter-effective, if tasks are distributed to multiple processors located on a high number of different PSs, the overhead will be significantly increased. Keeping this in mind, our paper tries to reduce that overhead as much as possible to address the following issues: Scheduling
4. Problem Formulation and Solution

Task scheduling [18] on a target system having a network topology is defined as the problem of allocating the tasks of an application to a set of processors that have diverse processing capabilities in order to minimize total execution time. Thus, the input of task scheduling includes a task graph and a process graph. The output is a schedule representing the assignment of a processor to each task node.

4.1 Problem Formulation

In this section, we first define the terms used and then formulate the problem. Eventually, a genetic method for task scheduling is presented to solve the above mentioned problems.

![Fig. 4. A sample DAG and a processor graph](image-url)

Definition 1. A task graph (e.g. as in Fig. 4a) is represented by a Directed Acyclic Graph (DAG), $G = (V, E, w, c)$, where the set of vertices $V = \{v_1, v_2, \ldots, v_k\}$ represents the set of parallel subtasks, and the directed edge $e_{ij} = (v_i, v_j) \in E$ describes the communication between subtasks $v_i$ and $v_j$, $w(v_i)$ associated with task $v_i \in V$ represents its computation time and $c(e_{ij})$ represents the communication time between task $v_i$ and task $v_j$ with corresponding transferred data $d(e_{ij})$. We presume that a task $v_i$ without any predecessors, $\text{prec}(v_i) = 0$, is an entry task $v_{\text{entry}}$, and a task that does not have any successors, $\text{succ}(v_i) = 0$, is an end task $v_{\text{end}}$. The task consists of workload $w_{li}$, which delimits the amount of work processed with the computing resources. Besides, it also contains a set of preceding subtasks $\text{prec}(v_i)$ and a set of successive subtasks $\text{succ}(v_i)$ of task $v_i$, $t_s(v_i, P_j)$ denotes Start Time and $w(v_i, P_j)$ refers to the Execution Time of task $v_i \in V$ on processor $P_j$. Hence, the finish time of that task is given by $t_f(v_i, P_j) = t_s(v_i, P_j) + w(v_i, P_j)$.

Suppose that the following conditions are satisfied:

Condition 1. A task cannot begin its execution until all of its inputs have been gathered sufficiently. Each task appears only once in the schedule.

Condition 2. The ready time $t_{\text{read}}(v_i, P_j)$ is the time that processor $P_j$ completes its last assigned task and be ready to execute task $v_i$. Therefore,

$$t_{\text{read}}(v_i, P_j) = \max \left\{ \max_{v_i \in \text{prec}(j)} (t_s(v_i, P_j)), \max_{e_{ij}, v_i \in \text{exec}(j)} (t_f(e_{ij})) \right\},$$

(1)
where \( \text{exec}(j) \) is a set of tasks executed at processor \( P_j \), \( t_f(v_i) = t_f(v_{\text{ej}}) + c(v_{\text{ej}}) \) and \( \text{prec}(v_i) \) is a set of preceding tasks of \( v_i \).

**Condition 3.** Let \( [t_a, t_b] \subset [0, \infty] \) be an idle time interval on processor \( P_j \) in which no task is executed. A free task \( v_i \in V \) can be scheduled on processor \( P_j \) within \( [t_a, t_b] \) if

\[
\max \{ t_f, t_{\text{ready}}(v_i, P_j) \} + w(v_i, P_j) \leq t_b. \tag{2}
\]

**Definition 2.** A processor graph \( TG = (N, D) \) demonstrated in **Fig. 4b** is a graph that describes the topology of a network between vertices (processors) that are cloud virtual machines (VMs). In this model, \( N \) is the finite set of vertices, and a directed edge \( d_{ij} \in D \) denotes a directed link from vertex \( P_i \) to vertex \( P_j \) with \( P_i, P_j \in N \). Each processor \( P_i \) controls the processing rate \( p_i \) and bandwidth \( bw_i \) on the link connecting it to other processors.

**Problem Definition**

In this section, we make some assumptions about the proposed method. Only output data from each task node is stored as a saved state. The state containing the data will be transferred to the processors that execute the child nodes of the completed task nodes. When a PS failure occurs, the saved state can be found in the ancestor task node. We suppose only a single stop failure of a physical server. When it occurs, all processors in the server simultaneously stop their execution. Let \( t(S_1 + S_2, v_i) \) be the total time of an entire schedule \( S_1 + S_2 \) with a failure happening at this task \( v_i \), \( S_i \) be a schedule before the failure, \( S_2 \) be a schedule after the failure. Our purpose is to find and reallocate the last tasks in the critical path to multiple machines to minimize the entire schedule time and avoid the worst case. That means finding the schedule \( (S_1 + S_2) \) to minimize \( \max_{v_i \in F} t((S_1 + S_2), v_i) \).

**4.2 Proposed approach**

Given a task graph \( G = (V, E, w, c) \) and a processor graph with network topology \( TG = (N, D) \), our method uses a genetic algorithm to choose the most appropriate schedule to execute the tasks. Among the various guided random techniques, genetic algorithms (GAs) are the most widely used for the task scheduling problem [12].

![Fig. 5. Genetic algorithm](image-url)

A genetic algorithm [7], illustrated in **Fig. 5**, is inspired by natural evolution. It is a robust search technique that allows a global high-quality solution to be derived from a large search space in polynomial time. This is in contrast to other algorithms that find only local optimal results. GA combines the best solutions from past searches with exploration of new regions of the solution space. In this algorithm, a feasible solution is represented using an individual (chromosome), that is a set of task assignments. The algorithm keeps a population of these
randomly generated individuals that evolves over generations. The quality of an individual in the population can be characterized by a fitness function whose value specifies the fitness of an individual compared to others in the population. Higher fitness level present better solutions. Based on fitness, parents are selected to produce offspring for a new generation. The fitter individual has a better chance to reproduce. A new generation has the same number of individuals as the previous generation, which dies off once it is replaced with the new generation. By applying genetic operators, namely selection, crossover and mutation to a population of chromosomes, the quality of the chromosomes can be improved. As a result, a new population of individuals is produced. If well designed, this new population will converge to optimal solution. The following section describes in detail each operator of the genetic algorithm:

- **Representation**
  
  Here, we choose each individual (as shown in Fig. 6a) in the population to illustrate a feasible solution to the problem and contain an array of task assignments. Each of the assignments consists of a task and a corresponding assigned processor. The time frames of each task in each individual, such as Earliest Start Time, Earliest Finish Time, and so on, can be changed to adjust those of its successive tasks. These changes can lead to a very complex state during the genetic algorithm. Hence, our solution is to ignore the time frame while conducting genetic manipulation and assign a time slot to each assignment in order to obtain a feasible schedule later.

[Fig. 6. A one-dimensional array and two-dimensional array]

A one-dimensional array (Fig. 6a) may not be suitable for representing the workflow because it only defines which processor is allocated to each task and cannot show the order of task assignments on each processor. However, the execution order is very important since it significantly impacts the workflow execution [6]. We use a two-dimensional array to represent a schedule, as demonstrated in Fig. 6b. In this two-dimensional array, the order of tasks on each processor is shown. During genetic manipulation, the two-dimensional array is transformed into a one-dimensional array.

- **Establishing the Initial Population**

  The initial population is a set of individuals generated through a random heuristic. Each individual consists of pairs of tasks and processors on which the tasks are allocated.

- **Constructing a Fitness Function**

  A fitness function can be used to characterize the quality of each individual in a population based on its optimization value. According to fitness value, parents are selected to generate new offspring. Since the purpose of our method is to minimize the schedule length while considering the network contention and the cost for cloud users, the fitness function has to rely
on EFT and cloud costs paid by CSCs. The following section illustrates establishment of EFT and the cost of task $v_i$ on a processor from its start time as well as the ingredient costs.

The start time of a task is defined when the last preceding task is completed. Thence, to determine that start time, the earliest idle interval $[t_A, t_B]$ on processor $P_j$ has to be searched and found to satisfy condition 2 and condition 3. As a result, the start time $t_s$ of task $v_i$ on processor $P_j$ is set as:

$$t_s(v_i, P_j) = \begin{cases} \max(t_A, t_{ready}(v_i, P_j)), & \text{if } v_i \neq v_{entry} \\ 0, & \text{otherwise} \end{cases}$$

(3)

Thus, the Earliest Start Time (EST) of a task $v_i$ executed on a processors $P_j$ is computed as follows:

$$EST(v_i, P_j) = \max_{v_j \in \text{proc}(v_i), v \in \mathbb{N}} (t_f(v_j, P_j)) + \max_{t \in \mathbb{N}} (c(e_{ij})),$$

(4)

where $c(e_{ij})$ is the communication time between processors $P_k$ and $P_j$ to execute task $v_i$ and is defined as:

$$c(e_{ij}) = (d_{ij}^i + \sum_{v_{j} \in \text{proc}(v), v \neq \text{exec}(k, i)} d_{ij}^i) \cdot \left(\frac{1}{bw_j} + \frac{1}{bw_k}\right)$$

(5)

Here $d_{ij}^i$ is the amount of input data stored at processor $P_k$ and used for executing task $v_i$ and $d_{ij}^i$ is amount of outgoing data executed from $P_k$ then transferred to $P_j$. Therefore, Earliest Finish Time (EFT) of the task $v_i$ is calculated as:

$$EFT(v_i, P_j) = w(v_i, P_j) + EST(v_i, P_j).$$

(6)

In addition, the algorithm also considers the cost paid by cloud customers for using cloud resources to execute the tasks. The cost $C(v_i, P_j)$ for task $v_i$ executed at a VM $P_j$ is defined by:

$$C(v_i, P_j) = C_{\text{proc}} + C_{\text{wait}} + C_{\text{comm}} + C_{\text{disc}} + C_{\text{mem}}$$

(7)

In equation (7), each cost is calculated as follows:

Cost of processing is expressed as:

$$C_{\text{proc}} = c_1 \cdot \frac{w_{i}}{p_{j}},$$

(8)

where $c_1$ is the processing cost per time unit of workflow execution on processor $P_j$ with processing rate $p_j$.

Let $t_{\text{min}}$ be the finish time of the task which is completed first out of the parallel tasks and there is no available task after this one, $c_2$ be the waiting cost per time unit and $t_i$ be the finish time of the task $v_i$. Then the cost of waiting time is as:

$$C_{\text{wait}} = c_2 \cdot (t_i - t_{\text{min}}).$$

(9)

Suppose that the amount of money per time unit for transferring outgoing data from processor $P_j$ is $c_j$, then the cost of communication time is defined as follows:
We assume that the distribution of disconnection events between a cloud and clients is a Poisson distribution with parameter $\mu_T$, which represents the stability of the network. The expected number of arrivals over an interval of length $\tau$ is $E[NT] = \mu_T \tau$. Let $L$ be a random variable for the length of an offline event, $\mu_L$ be the mean length and $c_4$ be the disconnection cost per unit time. Therefore, the expected duration of a disconnection event, which can affect the processing time of task $v_i$, is $\mu_T \tau \mu_L$. Hence, the cost of disconnection can be derived as:

$$C_{\text{disc}}(v_i;P_j) = c_4 \left( \mu_T \tau \mu_L \right).$$

Let $c_5$ be the storage cost per data unit and $s_t$ be the storage size of task $v_i$ on processor $P_j$. Then the storage cost of task $v_i$ on processor $P_j$ is calculated as:

$$C_{\text{str}}(v_i;P_j) = c_5 \cdot s_t.$$  

Further, we compute the cost of using the memory of processor $P_j$ for task $v_i$ as follows:

$$C_{\text{mem}}(v_i;P_j) = c_6 \cdot s_{\text{mem}},$$

where $s_{\text{mem}}$ is the size of the memory used and $c_6$ is the memory cost per data unit.

Using this cost, we can calculate a fitness function that computes the tradeoff $U(v_i,P_j)$ between the cost and $EFT$ as:

$$U(v_i,P_j) = \text{Min} \sum_{v \in E(v_i;P_j), v \in v_{\text{exec}}(v_i;P_j)} \left( \frac{\text{cost}(v_i;P_j)}{\text{Max}[\text{cost}(v_i;P_j)]} \cdot \frac{\text{EFT}(v_i,P_j)}{\text{Max}[\text{EFT}(v_i,P_j)]} \right).$$

By considering the above fitness function that combines $\text{cost}(v_i;P_j)$ and $\text{EFT}(v_i,P_j)$, we can determine which individual in a population is the most appropriate to satisfy the function. This demonstrates that its combination of $\text{cost}(v_i;P_j)$ and $\text{EFT}(v_i,P_j)$ should be minimized.

- **Genetic Operators**
  - **Selection**
    
    New individuals are selected according to their fitness described by the utility function’s tradeoff value after being compared to others in the population. The chance of being selected as a parent is proportional to fitness, and is in inverse ratio to the tradeoff value. An individual whose tradeoff value is lower, is better than one with a higher tradeoff value. The fittest is considered as successive generation evolves. An excessively strong fitness selection bias can lead to sub-optimal solution.
  
  - **Crossover**
    
    Crossover operates at an individual level and is used to generate new offspring from two randomly selected individuals (parents) in the current population in order to result in an even better individual in the subsequent generation. There are three methods of crossover: single-point crossover, two-point crossover, and uniform crossover, for all of which the chance of crossover is between 0.6 and 1 in general. As shown in Fig. 7a, 7b and 8, the crossover operator used is determined by the following rules:
- One, two (or multiple) points are randomly chosen from selected parents.
- These random points divide each individual into left and right sections.
- Crossover then swaps the left (or the right) sections of the two individuals.
- Two new offspring are created by recombining sections taken from two parents.

![Fig. 7. Single-point crossover and two-point crossover](image)

Specially, a random mask containing bits (as illustrated in Fig. 8) is generated in uniform crossover. The mask determines which bits are copied from each parent. The bit represents the position of the elements in each individual, and the bit density in the mask determines how much materials is taken from each parent.

![Fig. 8. Uniform crossover](image)

**Mutation**

In genetic algorithms, a mutation generates new offspring from a single parent in the current population. Mutation maintains the diversity of individuals by exploring new and better genes than were previously considered in order to prevent a combination of all solutions in the population converging into a local optimum of solved problems as crossover can only explore the current combinations in the gene pool. However, mutation rates are low as the chance of mutation in a specific individual is low (approximately 0.001). There are two types of mutations: a replacing mutation and a swapping mutation.

![Fig. 9. Replacing mutation and swapping mutation](image)
The purpose of the replacing mutation is to reallocate a substitute processor to a random task in an individual. The selected processor is also randomly chosen and has enough capacity to execute the task. Fig. 9a illustrates the replacing mutation. In this figure, processor $P_2$ allocated to task $v_4$ is replaced by processor $P_4$. In contrast, the swapping mutation changes the execution order of independent tasks on the same processor in an individual for the same time slot. The example of swapping mutation in Fig. 9b shows that task $v_5$ occupies the initial time slot of task $v_6$.

To verify the performance of our proposed genetic algorithm based approach, we have also designed several other task scheduling algorithms. These algorithms minimize the schedule length of the workflow or lessen the cloud cost paid by CSCs. Algorithm 1 is Greedy for Cost algorithm, where each task of the workflow is assigned to a processor which minimizes cost greedily for Cloud resources to execute that task. In algorithm 2, Contention aware Scheduling [11] aims to create a schedule based on $EFT$ pondering on network contention. Interleaved method in algorithm 3 spreads tasks to professors of all PMs as much as possible. Meanwhile, algorithms 4,5 show that our approach takes into account both network contention and the cloud cost as well as the tradeoff between them. Moreover, our method also tries to get a global optimal scheduling of the workflow to reduce recovery time in case of failure.

**Algorithm 1. Greedy for cost algorithm**

**Input**: Task graph $G = (V, E, w, c)$, processor graph $TG = (N, D)$

**Output**: A new task scheduling

**Function** greedyForCostScheduling($G, TG$) 

{ 
    Sort task $v_n \in V$ into list $L$ according to priority 
    for each $v_n \in L$ 
    { 
        Find the best processor $P_j$ which minimize the execution cost of task $v_n$ 
        Assign $v_n$ on $P_j$ 
    } 
    return a new task scheduling 
}

**Algorithm 2. Network contention aware scheduling algorithm**

**Input**: Task graph $G = (V, E, w, c)$, processor graph $TG = (N, D)$

**Output**: A new task scheduling

**Function** contentionAwareScheduling ($G, TG$) 

{ 
    Sort task $v_n \in V$ into list $L$ according to priority 
    for each $v_n \in L$ 
    { 
        Find the best processor $P_j$ which allows $EFT$ of $v_n$, taking account of network bandwidth usage; 
        Assign $v_n$ on $P_j$; 
    } 
    return a new task scheduling; 
}
Algorithm 3. Interleaved scheduling algorithm

Input : Task graph \(G = (V, E, w, c)\), processor graph \(TG = (N, D)\)
Output : A new task scheduling

Function interleavedScheduling \((G, TG)\) {
\[
\text{Sort task } v_n \in V \text{ into list } L \text{ according to priority}
\]
\[
\text{Spread tasks to professors of all PSs as much as possible and processor } P_j \text{ executing task } v_n \text{ task has to allow EFT of } v_n
\]
return a new task scheduling
}

Algorithm 4. Cost-Time aware Genetic scheduling algorithm

Input : Task graph \(G = (V, E, w, c)\), processor graph \(TG = (N, D)\)
Output : A new task scheduling

Function geneticScheduling \((G, TG)\) {
\[
\text{Generate initial population}
\]
\[
\text{Compute fitness of each individual according to the equation (14)}
\]
repeat // New generation
\[
\text{Select two parents from old generation}
\]
\[
\text{Recombine parents for two offspring}
\]
\[
\text{Compute fitness of offspring}
\]
\[
\text{Insert offspring in new generation}
\]
until population has converged
return a new task scheduling
}

Algorithm 5. Minimum recovery time approach

Input : Task graph \(G = (V, E, w, c)\), processor graph \(TG = (N, D)\)
Output : A new task scheduling

Function minimizeRecoveryTime \((G, TG)\) {
\[
\text{for } (i = 1; i \leq \text{number of tasks in critical path})
\]
\[
S = \emptyset
\]
\[
S1 = \text{schedule generated by Cost-Time aware Genetic scheduling algorithm (Algorithm 4)}
\]
\[
\text{for } (\text{failtask} = 1 \text{ to number of all tasks})
\]
\[
\text{//Assuming failure happens at failtask}
\]
\[
\text{Find set } T \text{ of all tasks executed after recovery if task failtask fail}
\]
\[
S2 = \text{schedule is generated by Algorithm 4 with input is } T \text{ and available processors}
\]
\[
\text{Set } S' = S \cup (S1 \cup S2)
\]
\[
\text{int index} = 0
\]
\[
\text{Criticalpath[index++]} = \max_{v\in S'} \text{scheduleLength}(S)
\]
return the shortest element of the Criticalpath
}
5. Implementation and Analysis

In this section, we present experiments that analyze many aspects of our approach. To justify the efficiency of the proposed approach, the Cost-Time aware Genetic scheduling algorithm (CTaG), numerical simulations are used to evaluate it and compare its performance with those of other methods, in terms of monetary cost or network bandwidth. The compared methods include the well-known Contention-aware Scheduling (CaS) algorithm [11], the Greedy for Cost algorithm (GfC), the Interleaved Scheduling method (IS) and a Time aware Genetic scheduling (TaG) algorithm [23] keeping in view only processing time of the system.

5.1 Experimental Settings

All the parameters are different task graphs $G=(V, E, w, c)$ with the increase of the matrix sizes (10-60) and heterogeneous processor graphs $TG=(N, D)$ which is a combination between 30 VMs with the different configurations located at the local system of CSCs for the above algorithms as list in Table 2. We developed the simulations in Java with JDK-7u7-i586 and Netbeans-7.2 using CloudSim [16]. It is a framework for modeling and simulation of cloud computing infrastructures and services. In our simulation, we describe MI as Millions of Instructions and denote MIPS as Million Instructions per Second to represent the processing capacity of processors. Moreover, we define a sample of processing cost in Table 3, data transmission cost in Table 4, waiting cost and disconnection one in Table 5. It is obvious that the processing cost and transmission cost are inversely proportional to processing time and transmission time correspondingly. The I/O data of the task has a size from 100 to 500 MB.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network</td>
<td>LAN</td>
</tr>
<tr>
<td>Topology model</td>
<td>Fully Connected</td>
</tr>
<tr>
<td>Operating system</td>
<td>Windows 7 professional</td>
</tr>
<tr>
<td>Number of processors</td>
<td>[5, 30]</td>
</tr>
<tr>
<td>Number of tasks</td>
<td>[10, 90]</td>
</tr>
<tr>
<td>Processing rate</td>
<td>[10, 750] MIPS</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>10, 100, 512, 1024 Mbps</td>
</tr>
</tbody>
</table>

Table 2. Characteristics of the target system

<table>
<thead>
<tr>
<th>Processing rate (MIPS)</th>
<th>Cost per time unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>[10, 50]</td>
<td>0.6</td>
</tr>
<tr>
<td>[50, 125]</td>
<td>1.7</td>
</tr>
<tr>
<td>[125, 250]</td>
<td>3.6</td>
</tr>
<tr>
<td>[250, 500]</td>
<td>7.5</td>
</tr>
<tr>
<td>[500, 750]</td>
<td>11</td>
</tr>
</tbody>
</table>

Table 3. Processing rate and corresponding cost for executing a task at processor $P_j$

<table>
<thead>
<tr>
<th>Bandwidth (Mbps)</th>
<th>Cost per time unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0.01</td>
</tr>
<tr>
<td>100</td>
<td>0.1</td>
</tr>
<tr>
<td>512</td>
<td>0.52</td>
</tr>
<tr>
<td>1024</td>
<td>1.024</td>
</tr>
</tbody>
</table>

Table 4. Cost of data transmission
Table 5. Other costs

<table>
<thead>
<tr>
<th>Cost</th>
<th>Cost per time unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost of waiting time</td>
<td>[0.1, 0.4]</td>
</tr>
<tr>
<td>Cost of a disconnection time</td>
<td>[0.02, 0.2]</td>
</tr>
</tbody>
</table>

5.2 Experimental Results

The following figures show the simulation results of our proposed genetic method for task scheduling compared against other scheduling techniques. In the following figures, it is obvious to see that there are some differences between the simulated results. Fig. 10a shows that, in terms of schedule length, in an environment with no failure, as the number of tasks increases, our method is 27% better than GfC and 15% better than IS due to the extra communication between processors. This is because the proposed method can determine optimal schedules while considering network contention. Additionally, in Fig. 10b, when the system has a failure that increases the recovery time, some physical machines have to restart, which increases processing time in the workflow because some task nodes’ results are lost and must be reacquired. Our proposal produces a workflow schedule with better performance than others regardless of the number of tasks. Particularly, it achieves a greater than 13% increase in speed compared with the TaG and more than 38%, 18% increase compared with GfC, CaS, respectively.

![Fig. 10. Schedule length comparison without failure (a) and with failure (b)](image)

![Fig. 11. Cost comparison without failure (a) and with failure (b)](image)
Regarding the monetary cost paid by CSCs (as illustrated in Fig. 11a), it has been observed that in case of no failure, TaG and CaS have the highest cost, while GfC has the lowest cost but its performance is not good comparatively. The CTaG has an economic advantage compared with IS, which means that its effectiveness increases together with monetary cost. In the meantime, our solution is balanced between schedule length and cloud cost. As a matter of fact, when compared with TaG, our method can save about 19% cost for CSCs while performance reduction is not greater than 17%. Nonetheless, when a failure occurs, the graph in Fig. 11b shows that, when the number of tasks increases, TaG and CaS require the highest monetary cost, the GfC is intermediate and the proposed method has the lowest cost. Notably, the cost of our approach is 24%, 20% less than the cost of the TaG, CaS, respectively, and saves 17% when compared with the GfC cost.

![Fig. 12. Schedule length (a) and cost (b) with numbers of processors](image1)

We next measured the effect of increasing number of processors on the cloud cost and the schedule length only in CTaG with a fixed number of tasks. The results reflected in Fig. 12a and 12b indicate that more processors result in better system performance but higher cost. It is highly noticeable to find that the cost goes up from 300500 G$ to 325000 G$ as the number of processors increases from 15 to 20.

![Fig. 13. Schedule length (a) and cost (b) with numbers of individuals](image2)

Further, when the number of individuals is altered from 20 to 90 (Fig. 13a, 13b), we witness that the increase in the population size does not significantly affect the execution cost of the workflow while probability of finding a faster solution is higher. The cost just fluctuates
between 55000 and 60000 G$. On the other hand, scheduling time exhibits a downward trend from approximately 80 minutes to around 50 minutes. Finally, we observe the performance of the CTaG with different number of generations.

![Fig. 14. Schedule length (a) and cost (b) with numbers of generations](image)

Similar to the above simulation that regards the number of individuals, results from the Fig. 14a and 14b show that the schedule length of the workflow is reduced with slight decrease in the execution cost when the number of the generations increases. In particular, the schedule length drops dramatically from more than 290 minutes to 200 minutes when the number of generations increases from 20 to 40. This is because each individual selected considers the tradeoff between cloud cost and execution time.

5. Conclusion

In our study, we have presented an optimization and node recovery model for cloud computing, to improve the reliability of cloud services. We modeled our work through genetic task scheduling algorithm. The presented work can be very useful for large amount of data. The proposed model works in such a way that it distributes the tasks among the computing nodes in a datacenter on the basis of minimal scheduling length, hence, globally optimizing the overall process. In case of failure, the system is returned to its previous state in minimum possible time. Our model is cost-effective, since it considers the network bandwidth and the amount of money user has to pay for the services and the tradeoff between them. The presented simulation results and comparison with existing works justifies our model’s performance and efficiency. We intend to extend our work with more diverse and challenging scenarios to further extensively check the reliability of the system.

References


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