The Experiential Heterogeneous Earliest Finish Time Algorithm for Task Scheduling in Clouds

Artan Mazrekaj[1], Arlinda Sheholli[2], Dorian Minarolli[3] and Bernd Freisleben[4]
[1]Faculty of Contemporay Sciences and Technologies, SEEU University, Tetovo, Republic of North Macedonia
[2]Faculty of Electrical and Computer Engineering, University of Prishtina, Prishtina, Kosovo
[3]Faculty of Information Technology, Polytechnic University of Tirana, Tirana, Albania
[4]Department of Mathematics and Computer Science, University of Marburg, Marburg, Germany

Keywords: Cloud Computing, Task Scheduling, Resource Allocation.

Abstract: Task scheduling in cloud environments is the problem of assigning and executing computational tasks on the available cloud resources. Effective task scheduling approaches reduce the task completion time, increase the efficiency of resource utilization, and improve the quality of service and the overall performance of the system. In this paper, we present a novel task scheduling algorithm for cloud environments based on the Heterogeneous Earliest Finish Time (HEFT) algorithm, called experiential HEFT. It considers experiences with previous executions of tasks to determine the workload of resources. To realize the experiential HEFT algorithm, we propose a novel way of HEFT rank calculation to specify the minimum average execution time of previous runs of a task on all relevant resources. Experimental results indicate that the proposed experiential HEFT algorithm performs better than HEFT and the popular Critical-Path-on-a-Processor (CPOP) algorithm considered in our comparison.

1 INTRODUCTION

The Infrastructure-as-a-Service (IaaS) service model in cloud computing can be used to adjust the capacity of cloud resources depending on changing demands of applications. This feature is known as auto-scaling (Malawski et al., 2012).

Task scheduling in cloud infrastructures is the problem of assigning tasks to appropriate resources (Bailin et al., 2014). Task scheduling can have a significant impact on the performance of the system and is particularly challenging when the cloud resources are heterogeneous in terms of their computation, memory, and communication characteristics, due to different execution speeds, memory capacities, and communication rates between processors.

Typically, the scheduling process in the cloud consists of several phases (Choudhary and Peddoju, 2012): resource discovery and filtering, where a broker discovers the resources in the network and collects their status information; resource selection, where the target resources are selected, based on the main parameters of the task and the resources; task submission, where tasks are submitted to selected resources. Task scheduling algorithms select and allocate suitable resources to tasks such that the overall execution can be completed to satisfy objective functions specified by users or cloud providers (Singh and Singh, 2013; Cui and Xiaoqing, 2018). For example, to improve Quality of Service (QoS) for users and maximize profit for cloud providers, parameters such as resource utilization, throughput, performance, execution times, computational cost, bandwidth, energy consumption, and Service Level Agreements (SLAs) may be considered (Dubey et al., 2018).

The task scheduling problem can be classified into static and dynamic scheduling. In static scheduling, all information about tasks such as execution and communication costs for each task and the relationship with other tasks are known in advance. In dynamic scheduling, there is no prior information, i.e., decisions are made at runtime (Arabnejad and Barbosa, 2014).

In this paper, we present a novel dynamic task scheduling algorithm for cloud environments with heterogeneous resources. It extends the Heterogeneous Earliest Finishing Time (HEFT) algorithm by utilizing past experiences with task

Mazrekaj, A., Sheholli, A., Minarolli, D. and Freisleben, B.
The Experiential Heterogeneous Earliest Finish Time Algorithm for Task Scheduling in Clouds.
DOI: 10.5220/0007722203710379
In *Proceedings of the 9th International Conference on Cloud Computing and Services Science (CLOSER 2019)*, pages 371-379
ISBN: 978-989-758-365-0

executions, hence we call it the *experiential HEFT* (EHEFT) algorithm. It uses an additional parameter that calculates the minimum average execution time of previous runs of a task on all relevant resources. This parameter equips the proposed EHEFT with the ability to take the workload and processing power of resources into account when assigning a task to a processor. It gives priority to a resource that in the past has executed the task faster than others. Experimental results show that our EHEFT algorithm performs better and is more efficient than other than the original HEFT and the popular Critical-Path-on-a-Processor (CPOP) algorithm considered in our comparison.

This paper is organized as follows. Section 2 describes related work on task scheduling. In Section 3, the task scheduling problem is formulated. HEFT and CPOP are described in Section 4. Our novel EHEFT algorithm is introduced in Section 5. Experimental results are presented in Section 6. Section 7 concludes the paper and outlines areas for future work.

2 RELATED WORK

Several approaches have been presented in the literature to solve the problem of task scheduling. The general task scheduling problem is NP-hard (Garey and Johnson, 1979). Thus, research in this field focuses on finding suitable low-complexity heuristics that perform well.

Parsa and Entezari-Maleki (2009) have proposed a task scheduling algorithm called RASA (Resource Aware Scheduling Algorithm) that takes the scalability characteristics of resources into account. RASA is compared to two traditional scheduling algorithms, Max-Min and Min-Min, making use of their advantages and avoiding their disadvantages. RASA is more efficient in task scheduling and achieves better load balancing.

To achieve better results than RASA, an improved version of the Max-Min algorithm has been proposed Elzeki et al., (2012). Their improved Max-Min algorithm is based on the expected execution time as a basis for selecting tasks instead of completion time. This approach has resulted in better load balancing and smaller makespans than other algorithms used for comparison.

Hu et al., (2009) have proposed a probability dependent priority algorithm to determine the allocation strategy that requires the smallest number of servers to execute tasks.

Pandey et al., (2010) have proposed a scheduling strategy that is based on a Particle Swarm Optimization (PSO) algorithm to schedule applications to cloud resources. It takes computation cost and data transmission into account. The algorithm is compared to the existing heuristic algorithm 'Best Resource Selection' (BRS) where PSO can achieve three times of cost savings compared to BRS, and the best distribution of the workload to resources.

To schedule large-scale workflows with various QoS parameters, Chen and Zhang (2009) have proposed an Ant Colony Optimization (ACO) algorithm. The algorithm intends to find a solution that meets all QoS constraints and optimizes the user preferred QoS parameters.

Malawski et al., (2012) have addressed the issue of efficient management under budget and deadline constraints in IaaS clouds. They propose various static and dynamic algorithms for both task scheduling and resource provisioning. From the results it is evident that an admission procedure based on workflow structure and the task's estimated execution time can improve quality and performance. Their work considers only a single type of virtual machines (VM) and does not take heterogeneity of IaaS clouds into account.

Byun et al., (2011) have proposed an architecture for automatically executing large-scale workflow applications on dynamically and elastically provisioned computing resources. The authors describe an algorithm that estimates the optimal number of resources to execute a workflow within a user specified finish time. The algorithm also generates a task to resource mapping and is designed to run online. This approach considers the elasticity of cloud resources, but does not consider the heterogeneity of computing resources.

Rodriguez and Buyya (2014) have proposed a resource provisioning and scheduling strategy for scientific workflows in cloud infrastructures. The authors model this strategy through Particle Swarm Optimization, to optimize the total execution cost while meeting deadline constraints. In their model, there are some IaaS cloud properties such as heterogeneity, elasticity, and dynamicity of resources. Moreover, performance variations and VM boot time parameters are considered.

Canon et al., (2008) have analyzed 20 directed acyclic graph (DAG) scheduling heuristics by investigating how robustness and makespan are correlated. The authors address the issue whether dynamically changing the order of tasks on their processors can improve robustness. The authors

conclude that the HEFT algorithm is one the best algorithms in terms of robustness and schedule length.

In contrast to the existing task scheduling approaches presented above, we propose a novel approach as an extended version of the HEFT algorithm that takes the workload of resources depending on experiences with previous executions of tasks into account. In the following sections, we explain task scheduling in general and the CPOP and HEFT algorithms in particular to motivate the design of our novel algorithm.

3 TASK SCHEDULING

To divide an application into tasks with appropriate sizes, we use DAGs. Each task of a DAG corresponds to the sequence of operations and a directed edge represents the dependency between the tasks.

More precisely, a DAG is represented by the graph $G = (V, E)$, where V is the set of v tasks and E is the set of e edges between the tasks. Each edge $(i, j) \in E$ represents the dependency such that task n_i should complete its execution before task n_j starts.

If a task has no a parent task, this task is defined as the entry task of a workflow of tasks. If a task has no a child, this task is defined as the exit task of a workflow of tasks.

From the DAG, we derive a matrix W that is a $v \times p$ computation cost matrix, where v is the number of tasks and p is the number of processors; $w_{i,j}$ represents the estimated execution time to complete task v_i on processor v_j. The average execution time of task v_i is defined in Equation (1) (Llavarasan and Thambidurai, 2007; Arabnejad and Barbarosa, 2014):

$$\overline{w}_i = \frac{\sum_{j \in P} w_{i,j}}{p} \quad (1)$$

Each edge $(i, j) \in E$ is associated with a non-negative weight $c_{i,j}$ which represents the communication cost between task v_i and v_j. The average communication cost of an edge (i, j) is defined in Equation (2):

$$\overline{c}_{i,j} = \overline{L} + \frac{data_{i,j}}{\overline{B}} \quad (2)$$

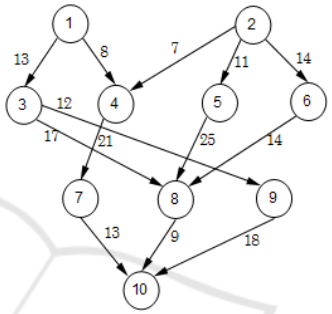
$\overline{L}$ is the average communication startup time, and $\overline{B}$ is the average transfer rate among the processors; $data_{i,j}$ is the amount of data required to be transmitted from task v_i to task v_j. In cases when tasks v_i and v_j are scheduled to run on the same processor, the communication cost is considered to be zero, because the intra-processor communication cost is negligible compared to the inter-processor communication cost.

A task workflow example and a computation cost matrix of tasks 1-10 for the resources R1, R2, R3 is shown in Figure 1.

An popular metric in task scheduling is the makespan or schedule length, which defines the finish time of the last task in the given DAG. The makespan is defined in Equation (3):

$$makespan = \max\{AFT(n_{exit})\} \quad (3)$$

where $AFT(n_{exit})$ represents the Actual Finish Time of the exit node.



Task	R1	R2	R3
1	11	12	17
2	18	21	15
3	8	10	13
4	17	11	19
5	11	5	14
6	21	12	7
7	18	20	12
8	15	8	13
9	11	19	15
10	23	9	14

Figure 1: An example of a task graph and a computation time matrix of the tasks for each resource.

Furthermore, the Earliest Start Time $EST(n_i, p_j)$ of a node n_i on a processor p_j is defined in Equation (4):

$$EST(n_i, p_j) = \max\{T_{avail}(p_j), \max_{n_m \in pred(n_i)} (AFT(n_m) + c_{m,i})\} \quad (4)$$

where T_{avail} is the earliest time at which processor p_j is ready to execute the task. $pred(ni)$ is the set of immediate predecessor tasks of task n_i. The inner max block in the EST equation denotes the time at which all data needed by n_i arrive at processor p_j. The communication cost $c_{m,i}$ is zero if the predecessor node n_m is assigned to processor p_j.

Finally, $EFT(n_i,p_j)$ defines the Earliest Finish Time of a node n_i on a processor p_j, which is defined in Equation (5):

$$EFT(n_i, p_j) = EST(n_i, p_j) + w_{i,j} \quad (5)$$

4 CPOP AND HEFT

In this section, we describe two popular algorithms for task scheduling, namely the Critical-Path-On-a-Processor (CPOP) and the Heterogeneous-Earliest-

Finish-Time (HEFT) algorithms (Topcuoglu et al., 2002; Arabnejad and Barbosa, 2014).

Canon et al., (2008) have compared 20 scheduling algorithms and have concluded that both algorithms perform well, but the HEFT algorithm is the best algorithm in terms of makespan. Topcuoglu et al. (Topcuoglu et al., 2002) also consider the HEFT algorithm among the best list-based heuristic algorithms, and use the CPOP algorithm, among others, for comparison.

In both algorithms, the tasks are ordered based on a scheduling priority defined by a ranking function. The rank value for an exit task n_i is:

$$rank(n_i) = \overline{w}_i \tag{6}$$

For other tasks, the rank values are computed recursively based on the Equations (1), (2) and (6), as defined in Equation (7):

$$rank(n_i) = \overline{w}_i + \max_{n_j \in succ(n_i)} (\overline{c}_{i,j} + rank(n_j)) \tag{7}$$

where $succ(n_i)$ is the set of immediate successors of task n_i, $\overline{c}_{i,j}$ is the average communication cost of edge (i, j), and $\overline{w}_i$ is the average execution time of task n_i.

4.1 CPOP

The CPOP algorithm consists of two phases: task prioritization and processor selection.

The task prioritization phase assigns the priority of each task by computing the rank values for all tasks. In CPOP, for a given application the graph uses a critical path, where the length of this path is the sum of the communication costs of the tasks on the path and the communication costs between the tasks along the path. The sum of rank values set the priority of each task. Initially, the entry task is the selected task and marked as a critical path task. An immediate successor (of the selected task) that has the highest priority value is selected and is marked as a critical path. This process is repeated until the exit node is reached (Topcuoglu et al., 2002). In the processor selection phase, the task that has the highest priority is selected for execution. If the selected task is on the critical path, it will be scheduled on the critical path processor. Otherwise, the task is assigned to a processor that minimizes the earliest execution finish time. The CPOP algorithm has $O(v^2 \times p)$ time complexity, where v is the number of tasks and p is the number of processors (Llavarasan and Thambidurai, 2007; Arabnejad and Barbosa, 2014).

4.2 HEFT

Similarly, the HEFT algorithm also has the same two phases: task prioritization and processor selection (Topcuoglu et al., 2002; Arabnejad and Barbosa, 2014).

In the task prioritization phase, HEFT assigns the priorities of all tasks by computing the rank for each task, which is based on mean computation time and mean communication cost. The task list is ordered by decreasing of their rank values.

The processor selection phase schedules the tasks on the processors that give the Earliest Finish Time (EFT) for the task. The algorithm uses an insertion policy that tries to insert a task at the earliest idle time between two already scheduled tasks on a processor. The slot should have enough capacity to accommodate the task.

The HEFT algorithm also has $O(v^2 \times p)$ time complexity, where v is the number of tasks and p is the number of processors (Topcuoglu et al., 2002; Llavarasan and Thambidurai, 2007; Arabnejad and Barbosa, 2014).

5 EXPERIENTIAL HEFT

We now present a novel task scheduling algorithm, called experiential HEFT (EHEFT), which gives the original HEFT algorithm the ability to take the workload and computational power of resources into account when assigning a task to processor. In the EHEFT algorithm, the average execution time of a task is calculated by the definition given in Equation (1). Furthermore, the calculation of the average communication cost is performed according to Equation (2). As an extension of Equation (7), we have added a parameter that calculates the rank by considering the minimum average execution time of the task on each relevant resource. This novel rank calculation is shown in Equation (8):

$$rank(n_i) = \overline{w}_i + \max_{n_j \in succ(n_i)} (\overline{c}_{i,j} + rank(n_j)) + \min_{j \in R} \frac{\sum_{i=0}^{n_j} w_{i,j}}{n_j} \tag{8}$$

where R represents the set of processors; j is a processor of the set of processors. The execution time of the task i on processor j is defined by $w_{i,j}$, while the number of previous executions of the task in processor j is defined by n_j.

The proposed EHEFT algorithm is shown in Algorithm 1.

To prioritize processors that have executed a given task in a more efficient manner in the past, a sum and a count of previous execution times of tasks for each of the resources in the cloud is stored. When there is no such data, the EHEFT algorithm performs exactly as the HEFT algorithm itself. Therefore, the EHEFT algorithm we propose is highly dependent on the values of the past execution times of tasks.

Algorithm 1: Experiential HEFT Algorithm.

```
1:  Compute the computation cost for each
    task according to Eq.(1)
2:  Compute the communication cost of
    edges according to Eq.(2)
3:  Compute the average execution time of
    previous runs:
     for each task
        for each machine do
          sum up the time of the task's
          previous executions in the
          assigned processor
        end for
4:     Calculate the minimum as the
       proportion of the sum of Step 3 and
       the number of executions of a task
       in the assigned processor
5:   end for
6:  Compute the rank value for each task
    according to Equation (8)
7:  Sort the tasks in a scheduling list by
    decreasing order of task rank values
8:   while there are unscheduled tasks in
           the list
9:      Select the first task i from the
        list
        for each processor m do
           Compute the EFT(i,m) value
        end for
       Assign task i to processor m that
       minimized EFT of task i.
10:  end while
```

Assuming a high heterogeneity between cloud resources, variable processing powers, and workloads, as well as taking into account that some tasks are better suited for a particular processor architecture than others, by including the minimum average execution time of previous runs of a task in the resources of the cloud, the EHEFT algorithm gives precedence to a processor that has performed better in executing a given task in the past.

6 EXPERIMENTAL RESULTS

We now present experimental results of our proposed EHEFT algorithm compared to the existing HEFT and CPOP algorithms. The tests were conducted on an Intel Core i7-6500U CPU with a 2.50 GHz × 4 speed, 16 GB of RAM, on Ubuntu 16.04 LTS.

To evaluate the performance of the EHEFT algorithm, task graphs that were generated randomly are considered. We have implemented and simulated the three algorithms using the Python programming language. Our simulator has five input parameters: the number of resources (i.e., processors) in the cloud, the number of DAG nodes (i.e., tasks), connections between tasks, resource heterogeneity, and previous run statistics for each task. For simplicity, constant values are set for the average computational and communication costs. The simulator defines a set of virtual resources with heterogeneous processing powers, as well as current computational workloads and communication costs for the given input DAG. Resource heterogeneity is achieved by setting the *Beta* parameter in the simulator. Its value defines the ratio of the differences of processing powers between resources in the cloud.

The simulator is fed with different input values to test the variance of the algorithm in terms of makespan and runtime under different conditions. During our tests, the following parameters were used:

Beta = {0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0}

Number of DAG Tasks = {5, 10, 15, 20, 25}

Connectivity = {0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0}

Number of Processors = {2, 3, 4, 5, 6}

Our experiments are run for each of the tasks in each of the processors. Such test runs were performed to collect statistics for the execution times that were then used to calculate the minimum average execution time for past runs of a given task on all cloud resources. To avoid that this additional parameter biases the ranking function, a scaling parameter is used. This scaling parameter determines the weight of the minimum average execution time for past runs in the overall calculation of the rank. For all compared algorithms, the simulation conditions were the same. We use the following performance metrics for our evaluation of the proposed approach.

6.1 Scheduling Length Ratio (SLR)

To evaluate a schedule for a single DAG, the most commonly used metric is the makespan. The makespan represents the finish time of the last task in the scheduled DAG, as shown in Equation (3). Considering that a large set of task graphs with different properties is used, the schedule length should be normalized to a lower bound, which is known as the Schedule Length Ratio (SLR), defined in Equation (9).

$$SLR = \frac{makespan}{\sum_{n_i \in CP_{MIN}} \min_{p_j \in Q} \{w_{i,j}\}} \quad (9)$$

The denominator in the SLR metric is the minimum computation cost of the critical path tasks, represented as CP_{MIN}.

Figures 2-5 show the makespan of the three algorithms calculated by the example task graph and computation time matrix of the tasks in each processor of Figure 1.

The calculation of the makespan is performed for (a) Number of Tasks (Figure 2), (b) Connectivity (Figure 3), (c) Number of Processors (Figure 4), and (d) Processor Range (Figure 5).

In Figure 2, the simulations are run for five different DAG nodes, with an increasing number of nodes. As expected, the makespan increases with the number of nodes for each of the algorithms we evaluated. EHEFT performs better than the other algorithms, because it considers the heterogeneity of resources when calculating the rank for a task. It assigns the execution of a task to a resource that not only has the best present conditions to achieve the earliest finish time, but that has also shown to do so in the past.

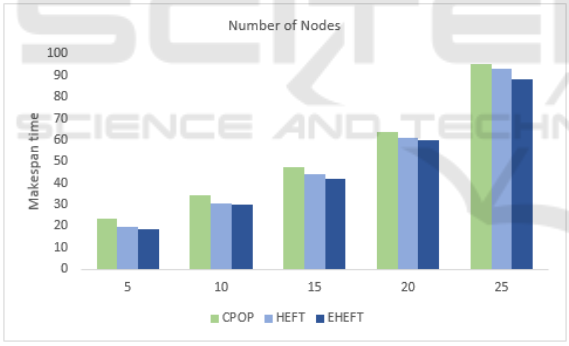


Figure 2: Makespan for Number of Tasks.

Figure 3 shows that increasing the connectivity between nodes of the input DAG also increases the makespan of the algorithms linearly. The higher the number of dependent tasks on the graph, the more time it takes for the algorithm to assign and execute the tasks.

Therefore, it is important to assign tasks that are part of critical paths to resources that can execute them in the fastest manner. In our simulations, we have put more load on the tasks in the critical path. Thus, the results indicate the ability of EHEFT to assign such tasks to resources with the highest processing power.

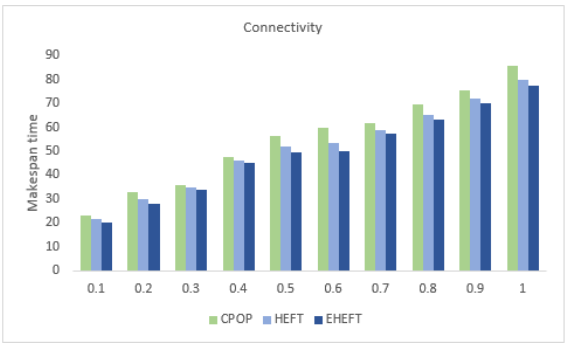


Figure 3: Makespan for Connectivity.

Figure 4 shows that increasing the number of processors and a constant node number for the input DAG decreases the makespan. The improvement in performance of the EHEFT algorithm is due to the variance in the calculation of the rank that the statistics of previous runs provide.

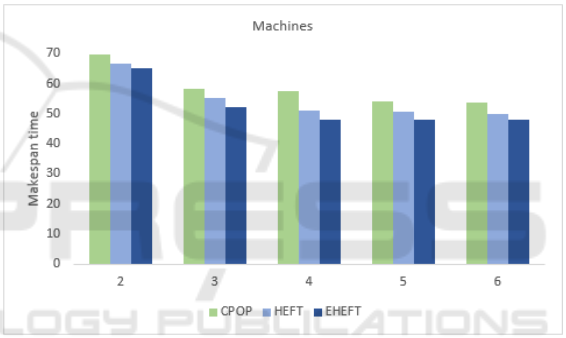


Figure 4: Makespan for Number of Processors.

The main advantage of EHEFT over HEFT and CPOP is the processor range parameter *Beta*, as shown in Figure 5. EHEFT considers the processing efficiency of a resource for a task, given its previous run statistics. The performance of EHEFT improves with the increase of the processor range, because it is the factor that makes the highest difference with respect to the average past execution time parameter.

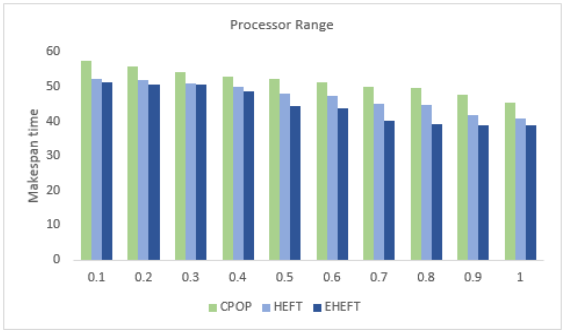


Figure 5: Makespan for Processor Range.

In Figure 6, we present the SLR value for each of algorithms calculated from the number of nodes. The graph shows that the SLR value for EHEFT is lower than for the HEFT and CPOP algorithms.

6.2 Runtime

The runtime metric represents the execution time to obtain the output of a schedule for a given task graph.

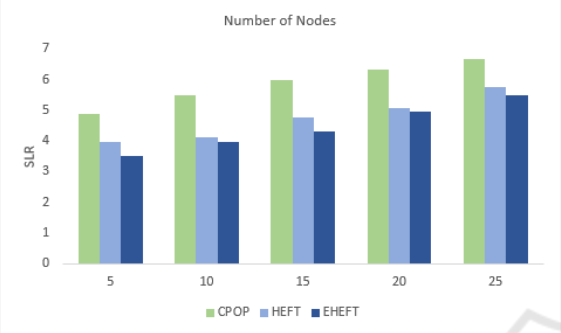


Figure 6: Scheduling Length Ratio.

The results for the runtimes of our performed experiments are shown in the graphs below.

Figures 7-10 show the runtimes of each of the algorithms calculated for the parameters (a) Number of Tasks (Figure 7), (b) Connectivity (Figure 8), (c) Number of Processors (Figure 9), and (d) Processor Range (Figure 10).

Figure 7 shows that for small numbers of DAG nodes the difference in runtime between EHEFT and HEFT is small. The improvement in performance that the minimum average execution time of the task for each resource gives is only apparent when the number of nodes in the input DAG increases.

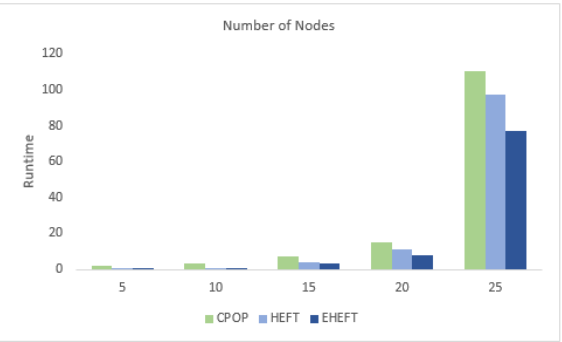


Figure 7: Runtime for Number of Tasks.

Figure 8 shows that increasing the connectivity between the nodes in the graph results in an increased runtime for the algorithms. The small difference in performance between EHEFT and HEFT is due to the difference in the handling of critical path tasks in the overall runtime. The CPOP algorithm takes more time to execute due to its two phase rank calculation.

As shown in Figure 9, task assignment and execution are performed in a faster manner with an increasing number of simulated virtual resources, as indicated by the decrease in the runtimes of the algorithms. The EHEFT algorithm gains an edge in performance due to its ability to assign the heavy loaded tasks and the ones in the critical path to better performing resources.

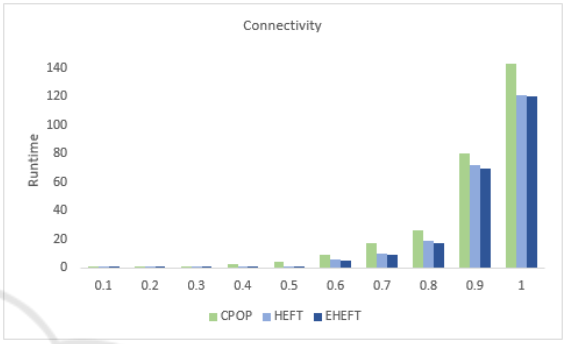


Figure 8: Runtime for Connectivity.

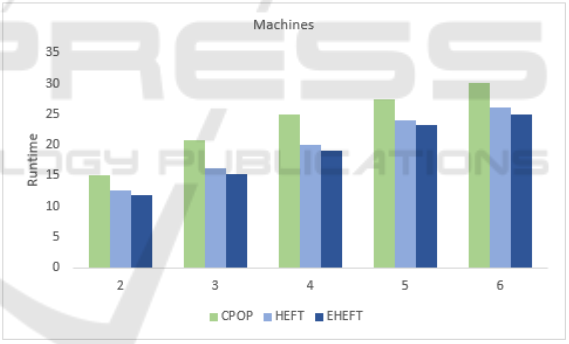


Figure 9: Runtime for Number of Processors.

Figure 10 shows that increasing the processor range improves the performance of all the algorithms that we evaluated. Since the CPOP algorithm assigns only tasks on the critical path to critical path processors, the EHEFT and HEFT algorithms show better results due to the fact that not only critical path tasks may be assigned to high performance resources. Tasks that take more time to process and that are not on the critical path of the graph are better assigned to resources through the HEFT and EHEFT algorithms. The difference in performance between the EHEFT and HEFT algorithm lies in the fact that EHEFT assigns tasks to resources that were better suited to execute such tasks in the past.

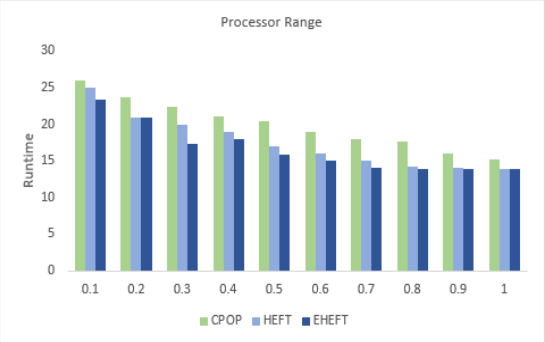


Figure 10: Runtime for Processor Range.

7 CONCLUSION

In this paper, we have presented a novel task scheduling algorithm for cloud environments, called Experiential Heterogeneous Earliest Finish Time (EHEFT) algorithm. In EHEFT, we have modified the rank calculation of the original HEFT algorithm by adding a parameter that specifies the minimum average execution time of a task on each relevant resource. The EHEFT algorithm performs better than the original HEFT and CPOP algorithms in terms of scheduling length ratio and runtime.

There are several areas for future research. First, we will investigate and experimentally evaluate other heuristic algorithms for task scheduling that consider the priority of tasks. Second, for more efficient task scheduling, other factors such as availability and scalability should be considered. Finally, it would be interesting to investigate multi-criteria and other workflow-aware strategies in cloud environments, including multiple virtual machine types and cloud deployment models.

REFERENCES

Arabnejad, H., and Barbosa, J. G. (2014). List Scheduling Algorithm for Heterogeneous Systems by an Optimistic Cost Table. *IEEE Transactions on Parallel and Distributed Systems*, 25(3), pages 1-14.

Bailin, P., Yanping, W., Hanxi, L., and Jie Q. (2014). Task Scheduling and Resource Allocation of Cloud Computing Based on QoS. *Advanced Materials Research*, Vols. 915-916, pages 1382-1385.

Byun, E. K., Kee, Y. S., Kim, J. S., and Maeng, S. (2011). Cost Optimized Provisioning of Elastic Resources for Application Workflows. *Future Generation Computer Systems*, 27(8), pages 1011–1026.

Canon, L.C., Jeannot, E., Sakellariou, R. and Zheng, W. (2008). Comparative Evaluation of the Robustness of DAG Scheduling Heuristics. *Grid Computing - Achievements and Prospects*, edited by Sergei Gorlatch, Paraskevi Fragopoulou and Thierry Priol, pages 73-84. Springer.

Chen, W. N. and Zhang, J. (2009). An Ant Colony Optimization Approach to a Grid Workflow Scheduling Problem with Various QoS Requirements. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, 39(1), pages 29-43.

Choudhary, M., and Peddoju, S. K. (2012). A Dynamic Optimization Algorithm for Task Scheduling in Cloud Environment. *Journal of Engineering Research and Applications (IJERA)*, 2(3), pages 2564-2568.

Cui, Y., and Xiaoqing, Z. (2018). Workflow Tasks Scheduling Optimization Based on Genetic Algorithm in Clouds. *3rd IEEE International Conference on Cloud Computing and Big Data Analysis (ICCCBDA)*, pages 6-10. IEEE.

Dubey, K., Kumar, M., and Sharma, S.C. (2018). Modified HEFT algorithm for Task Scheduling in Cloud Environment. *Procedia Computer Science*, Volume 125, pages 725-732. Elsevier.

Elzeki, O. M., Reshad, M.Z., and Elsoud, M.A. (2012). Improved Max-Min Algorithm in Cloud Computing. *International Journal of Computer Applications*, 50(12):22-27.

Garey, M. R., and Johnson, D. S. (1979). Computers and Intractability; A Guide to the Theory of NP-completeness. 1979.

Hu, Y., Wong, J., Iszlai, G., and Litoiu M. (2009). Resource Provisioning for Cloud Computing. *Conference of the Centre for Advanced Studies on Collaborative Research, CASCON '09*, pages 101-111. ACM.

Llavarasan, E., and Thambidurai, P. (2007). Low Complexity Performance Effective Task Scheduling Algorithm for Heterogeneous Computing Environments. *Journal of Computer Sciences*, 3(2), pages 94-103.

Malawski, M., Juve, G., Deelman E., and Nabrzyski J. (2012). Cost- and Deadline-Constrained Provisioning for Scientific Workflow Ensembles in IaaS Clouds. *Proceedings of the International Conference on High Performance Computing, Networking, Storage and Analysis*, pages 1–11.

Pandey, S., Wu, L., Guru, S. M., and Buyya, R. (2010). A Particle Swarm Optimization-based Heuristic for Scheduling Workflow Applications in Cloud Computing Environments. *In 24th IEEE International Conference on Advanced Information Networking and Applications (AINA)*. IEEE.

Parsa, S., and Entezari-Maleki, R. (2009). RASA: A New Task Scheduling Algorithm in Grid Environment. *World Applied Sciences Journal*, 7 (Special Issue of Computer & IT), pages 152-160.

Rodriguez, M. A., and Buyya, R. (2014). Deadline Based Resource Provisioning and Scheduling Algorithm for Scientific Workflows on Clouds. *IEEE Transactions on Cloud Computing*, 2(2), pages 222-235.

Singh, L., and Singh, S. (2013). A Survey of Workflow Scheduling Algorithms and Research Issues.

International Journal of Computer Applications, 74(15), pages 21-28.

Topcuoglu, H., Hariri, S., Wu, W. Min-You. (2002). Performance-Effective and Low-Complexity Task Scheduling for Heterogeneous Computing. *IEEE Transactions on Parallel and Distributed Systems*, 13(3), pages 260-274.