Novel Dynamic Load Balancing Algorithm for Cloud-Based Big Data Analytics

Arman Aghdashi | Seyedeh Leili Mirtaheri*

1Department of Electrical and Computer Engineering, Faculty of Engineering, Kharazmi University, Tehran, Iran

Correspondence
*Seyedeh Leili Mirtaheri, Email: Mirtaheri@khu.ac.ir

Abstract
Big data analytics in cloud environments introduces challenges such as real-time load balancing besides security, privacy, and energy efficiency. In this paper, we propose a novel load balancing algorithm in cloud environments that performs resource allocation and task scheduling efficiently. The proposed load balancer reduces the execution response time in big data applications performed on clouds. Scheduling, in general, is an NP-hard problem. In our proposed algorithm, we provide solutions to reduce the search area that leads to reduced complexity of the load balancing. We recommend two mathematical optimization models to perform dynamic resource allocation to virtual machines and task scheduling. The provided solution is based on the hill-climbing algorithm to minimize response time. We evaluate the performance of proposed algorithms in terms of response time, turnaround time, throughput metrics, and request distribution with some of the existing algorithms that show significant improvements.

KEYWORDS: Cloud Computing, Big Data, Real-time Processing, Load Balancing, Distributed system, Scheduling, Resource Allocation, Optimization

1 | INTRODUCTION
Cloud computing is introduced as a new computing paradigm in which a pool of scalable and virtualized resources delivered as a computing service through communications networks such as local area networks and the Internet4. Cloud computing is a distributed computing approach that uses the high-speed Internet to transfer tasks from personal computers to remote clusters to minimize the cost of using resources by service providers, reduce application runtime, and maximize service revenue from client applications. Cloud computing traditionally provides services for users including infrastructure as a service (IaaS), platform as a service (PaaS) and software as a service (SaaS). Recently, new services such as data as a service (DaaS) and big data as a Service (BDaaS) were introduced5,6.

Big data consists of extensive datasets that volume, variety and velocity are fundamental its characteristics and require a scalable architecture for efficient processing4. Different applications make use of distinctive type therefore, the type of computing models applicable depends on the nature of the application, some applications require batch processing, others need real-time data processing that mostly many of them have real-time nature4,5,2. Big data processing requires scalability, fault tolerance and availability. Cloud computing delivers all these through hardware virtualization. Big data and cloud computing are two compatible concepts with a core focus on scalability, agility, and on-demand availability2. Cloud computing is a suitable solution to the requirements of big data analytics solutions considering the scalable, flexible and elastic resources4.
Efficient deploying of resources requires communication between different components of the system, which may cause bottlenecks in the network and an unbalanced load in a distributed system so that some resources are overused while other resources may not be used. One of the challenging issues in load balancing is the distribution of workloads on existing resources so that the system achieves maximum throughput with minimum available response time.

Big data analytics requires infrastructures with high-performance computing systems to perform. Many believe that cloud computing can be an excellent platform for storing and processing big data. With the increasing number of users and clients and facing ever-growing volumes of data, resource allocation and scheduling for load balancing have become an essential issue in homogeneous and heterogeneous physical machines in the clouds.

The system structure for big data analytics in the cloud environments includes subsystems for decision making, gathering, and analysis, with a large number of servers to manage vast volumes of data flow. Therefore, big data processing in the cloud requires efficient, effective, productive and reliable resources performed with maximum throughput and minimized energy consumption and runtime.

In this paper, we propose a novel load balancing algorithm in cloud environments for cloud service scheduling in system level that performs resource allocation and task scheduling efficiently. Scheduling in system level deal with management of resources in data centers so user requests are managed and tasks are distributed among virtual machines at this level which a proper method has a great impact on system performance. To support the supply of resources at run time, the proposed model first performs the resource allocation to virtual machines followed by task scheduling.

Our approach propose a novel load balancing algorithm that performs both resource allocation to virtual machines in a dynamic manner and task scheduling. The main contributions are summarized as follows:

- We propose a novel load balancing algorithm in cloud environments that performs resource allocation dynamically and task scheduling efficiently with real-time or near-real-time processing time for big data processing. The proposed load balancer reduces the execution response time in big data applications performed on clouds.
- We consider factors including CPU, memory, bandwidth, and workload level of processing nodes with considering scalability and availability for decision making and selecting the appropriate nodes to allocate resources and process tasks based on the mentioned factors.
- We recommend two mathematical optimization models to perform resource allocation and task scheduling and provide the solution based on the hill-climbing algorithm. This algorithm adjusts the quality of solution in order to avoid falling into that local optimum.
- We evaluate the performance of proposed method in compared with round robin, FCFS (FIFO), Max-min, Min-min, minimum execution time (MET) and genetic Algorithm (GA).

The rest of this paper is organized as follows. In section 2, we will review some of the existing and recent related articles. In Section 3, we will explain the proposed load balancing algorithm. Section 4 includes the system setup and evaluation results and finally, section 5 concludes the paper.

2 LITERATURE REVIEW

There are many of research work in load balancing to improve efficiency in cloud computing. Most of them improve response time, waiting time, make span, energy consumption, resource utilization and execution time. But some of them not consider other important parameters such as availability, speed and scalability. The complexity is reasoning to not consider these parameters. In order to avoid bottleneck and improve resource utilization cloud computing needs to load balancing to distribution of workloads on existing resources and dynamically balance the load among the nodes. Therefore, how to dynamically and efficiently allocate resources and task scheduling is a problem that needs to be solved.

Load balancing has attracted many researchers over the past decade. Load balancing algorithms could be divided into two categories that could be static or dynamic. In static algorithms, the traffic is equally divided between different nodes. Static algorithms are further categorized into sub-optimal and optimal. In optimal algorithms, the load balancer performs optimal assignments in a reasonable time. If the load balancer unit fails to calculate the optimal decision, the sub-optimal allocation is performed.
Static algorithm needs information about the number of task and existing resources and there is no need to monitor the resource when static algorithm is working, these types of algorithm when there is low variation in upcoming workload gives better results. The most well-known static algorithms are FCFS, round robin. In the FCFS job scheduling, the jobs are queued in the order of which come first and serving them by the order of their arrival demand of users. In round robin algorithm nodes allocate in equal portions and in circular order has to wait for their turn to execute their tasks, without considering the resource quantity of each server and the execution time of tasks. On the other hand, dynamic algorithm considers the real-time workload and response time of nodes with a dynamic feedback mode.

Contrary to static algorithms, decision making in dynamic algorithms depends on the status of the system during run-time and requires prior knowledge of system resources. Dynamic Load balancing with a set of policies and assignment tasks at runtime performs better in compared with static algorithms. However, in dynamic load balancing the workload of all resources needs to be continuously monitored that imposes extra overhead to each processor cycle. Therefore, the mentioned algorithms spend more time migrating tasks than doing useful tasks. Dynamic algorithms use the current state of the system, which uses a series of policies.

Algorithms that are in the focus group perform the task allocation and scheduling using a node, which collects all the information on the cloud network statically or dynamically. These algorithms reduce system overhead; however, they impose much more overhead on the node that performs the allocation and scheduling task.

Some of the most famous of dynamic load balancing algorithm can be mentioned are Minimum Execution Time (MET), Min–Min and Max–Min algorithms. Minimum Execution Time (MET) algorithm assigns tasks nodes based on the best execution time for that task which sometimes result to high load imbalance without regard to resource availability. Min-min and max-min algorithms estimate the execution and completion times of each of the tasks on each of the nodes. Min-min algorithm first determines the minimum completion times for each task on all nodes then selects the task with minimum completion time and assigns it to the resource on which the minimum execution time is achieved. The algorithm to the remaining tasks repeated same procedure until the all unscheduled tasks are wiped out. The Max-min algorithm, similar to the Min-min algorithm, after determining the completion times, firstly select task with maximum completion time is scheduled on the consistent machine in the case of max-min and the process is repeated until all the tasks are scheduled. The Max-min algorithm seems to do better than the Min-min whenever the number of small tasks is much more than the large ones, but in the other cases, early execution of the large tasks might increase the total response time of the system.

Kumar et al. proposed a conventional-based approach to balance the load and provide the horizontal scalability for the datacenter in cloud environment that distributes the load among all the virtual machines (VM) fairly. Objective is to utilize the cloud resource in effective way so that the execution speed of applications can increase. It developed a dynamic load balancing algorithm that not only utilizes the cloud resources properly and reduces the makespan time of tasks, but also provides the elasticity in cloud environment. Proposed algorithm not only minimizes the makespan time but also decreases the possibility of overload and under loaded of a virtual machine. Results proved that developed algorithm performs better than the existing algorithms in literature like Min-Min, SJF, and FCFS.

Li et al. proposed a task scheduling algorithm based on fuzzy clustering algorithms to reduce tasks waiting time. This paper constructs a task model, resource model, and analyze tasks’ preference, then classify resources with fuzzy clustering algorithms. Based on the parameters of cloud tasks, the algorithm will calculate resource expectation and assign tasks to different resource clusters, so the complexity of resource selection will be decreased. Combining kernel-based fuzzy c-means clustering algorithm and the improved FIFO algorithm to design a new scheduling algorithm. In the kernel-based fuzzy c-means clustering algorithm and used radial basis function (RBF) as the kernel function to calculate the similarity of the task and resources to assign tasks. As a result, the algorithm reduced tasks’ waiting time and improve the resource utilization.

Hamani et al. proposed a load balancing algorithm based on the weights of servers in the cloud platform. It suggested use of the fuzzy logic to represent the weight of the different nodes and implement separate requests in. The results show that this approach improved the load balancing process effectively and obtain much more improved results in processing time, cost of the virtual machines and response time.

Genetic algorithms, PSO, Ant colony, and Bee colony are metheuristic strategies that have tried to find a near-optimum solution by virtue of as to culminate in a better result. In the following, we will review a number of them in this category.

Saleh et al. proposed an enhanced scheduling algorithm, it based on the PSO algorithm and aims at scheduling a large number of tasks without affecting the system performance. In this paper, task scheduling algorithm IPSO has been proposed to run large-scale data in the cloud computing environment. The proposed algorithm divides the submitted tasks into a number of batches in a balanced and dynamic way. It considers two parameters which are, the number of tasks and the total length of tasks.
per each batch. It allocates a sub-optimal solution for each batch. Result show IPSO in minimizing makespan and improves the standard deviation and the degree of imbalance.

Sanaj et al. suggests a chaotic squirrel search algorithm (CSSA) to optimally multitask scheduling in an Infrastructure as a Service (IaaS) cloud atmosphere. The suggested chaotic squirrel search algorithm was ultimately synthesized with the messy local search to enable the exploring authority to complement Squirrel search algorithm (SSA) algorithms. It proposed an effective scheduling protocol should comply with user needs and aids a service provider perform excellent quality of service in order to boost general application efficiency and it was appropriate for cloud computing because the algorithm used system resources efficiently in order to decrease energy, expenses, resource consumption, time, and violation levels.

Samadi et al. proposed a load balancing strategy in heterogeneous cloud environments and propose a threshold-based load balancing algorithm that balances the load among data centers in cloud environments as well as minimizing remote communication among data centers. The proposed approach has two phases. Firstly, specify the load threshold of each data center based on its processing speed and storage capacity. Secondly, maintain load balancing among data centers based on this threshold while the proposed approach takes into consideration the heterogeneity of data centers. The results show that this approach improve sufficiently the load balancing among data centers and improves the performance of programs on the data centers geographically distributed by assigning client requests on multiple data centers and results show that this approach gives good result in balancing the load of data centers in a cloud environment.

Manikandan et al. suggest the combination of gravitational search algorithm and lion optimization search algorithm that are hybridized which serves as a multiple objective task scheduling. this paper explores one such solution that consumes lesser number of resources, having lower cost and consuming lesser energy. This model can reflect the demands of the tasks for the resources in detail. The multiple objective functions that is used in this paper is cost, energy, resource utilization, the scheduled time is also based on the multiple objective function. this paper proposes the idea of a hybrid LGSA algorithm that can evaluate and that could adjust the quality of solution in order to avoid falling into that local optimum. The algorithm balances cost, energy and resources depending upon the requirement of the end-user.

Mousavi et al. proposed hybrid load balancing algorithm for effective dynamic resource allocation in cloud based on Teaching-Learning-Based Optimization (TLBO) and Grey Wolves Optimization algorithms (GWO), which can well contribute in maximizing the throughput using well balanced load across virtual machines and overcome the problem of trap into local optimum. The evaluation of experimental results indicates the novel hybrid approach has better performance comparing to the existing algorithms, in particular, in high-volume data of cloud scheduler.

Vashishth et al. proposed a predictive scheme for task scheduling on the Cloud when the incoming data is high velocity, this approach used to task scheduling with the aim of reducing the overhead incurred when big data is processed on the cloud. Subsequently, it increases both the efficiency and reliability of the cloud network while handling Big Data. This paper presents a method of using classification in machine learning as a tool for scheduling tasks and assigning them to Virtual Machines (VMs) in the Cloud environment. Particle Swarm Optimization (PSO) is used to generate the dataset which is used to train the classifiers. A number of classification algorithms such as Naive Bayes, Random Forest and K Nearest Neighbor are then used to predict the VM best suited to a task in the test dataset. The appropriate choices of classifiers also give acceptable accuracy values for these small datasets. Load balanced allocation is achieved using the classifiers for allocation of tasks.

Lagwal et al. proposed new design based on Genetic Algorithm(GA) approach to make efficiently control of the cloud servers. For cost and time efficiency outputs in this paper first short processes according to the cost and the selected of VM are taken for creating new chromosome by crossover, with the help of Genetic algorithm. Then the broker assigns effective processes to clients on the basis of the cost and time. This method tried to balance the work-load by arranging VM on the basis of their processing power and arranging the cloudlets according to their Length. The list of VM and cloudlets is then submitted to broker for the allocation.

Abderraziq et al. proposed a new distributed load balancing algorithm, based on adaptive starvation threshold. It tries to balance the load between the servers while minimizing the response time of the cloud, maximizing the utilization rate of the servers, decreasing the overall migration cost, and maintaining the stability of the system. To achieve this objective, this method limits tasks migration when the VMs load is greater than an adaptive limit named starvation threshold. The threshold is updated regularly in order to take into consideration the idle time and the number of served requests. The experimental results showed that the proposed load balancing algorithm gives considerable performance gains when compared to the performance of the honey bee behavior(HBB) algorithm.

Tadi et al. proposed a load balancing algorithm that optimized workload distribution among virtual machines (VMs) considering the volume of workloads. This approach consists of two main algorithms: optimal workload scheduling among VMs
using BBO optimization and VM overload avoidance in the state of running of VMs by inspiring the banker algorithm. Experimental results reveal that this approach outperforms its counterparts in a heterogeneous environment when the resources are smaller than the workloads. Moreover, the utilization of physical resources gradually increases.

Many heuristic and meta heuristic dynamic algorithms exist for load balancing but all the algorithm have their limitations. However, to the best of our knowledge, no work from the literature review considers the nature of the big data applications which are served just by the scheduling. In this paper we propose a dynamic and efficient optimization-based load balancing algorithm with real-time or near-real-time processing time for big data processing on the cloud systems that performs resource allocation dynamically to virtual machines and task scheduling efficiently. We model the load balancing problem considering the response time and propose an optimized method to minimize response time and improve resource allocation with considering scalability and availability to select the appropriate node to allocate resources. Two mathematical optimization models are proposed to perform dynamic resource allocation to virtual machines and task scheduling. The provided solution is based on the hill-climbing algorithm to minimize response time. The solutions are provided to reduce the search area that leads to reduced complexity of the load balancing.

### 3 1 SYSTEM MODEL

This section describes the proposed system model. The proposed model falls under the category of centralized algorithms. We consider the cloud to be a set of data centers, each data center containing many physical machines (hosts), each with some virtual machines running the services requested by users. The tasks are performed at the request of users are known as system load. To achieve good performance and scalability, efficient balancing of workloads among resources and support the supply of resources at run time, the proposed model first performs the resource allocation to virtual machines followed by task scheduling.

#### 3.1 Resource Allocation to Virtual Machines

The resource allocation problem is modeled as the optimization problem presented in equation (1). The objective function of this model includes $V M_{i}^{pu}$, $V M_{i}^{mem}$, $V M_{i}^{bw}$ variables corresponding to the amount of the required processing unit, memory and bandwidth of ith virtual machine, respectively. The variables $P_{j}^{pu}$, $P_{j}^{mem}$, $P_{j}^{bw}$ are the amount of processing unit, memory, and bandwidth of the jth physical machine we are looking to maximize.

Maximize $(V M_{i}^{pu} / P_{j}^{pu}) + (V M_{i}^{mem} / P_{j}^{mem}) + (V M_{i}^{bw} / P_{j}^{bw})$

s.t. $\forall i \sum_{j=1}^{n} y_{ij} = 1$

$\forall j \sum_{i=1}^{n} y_{ij} V M_{i}^{pu} \leq P_{j}^{pu}$

$\forall j \sum_{i=1}^{n} y_{ij} V M_{i}^{mem} \leq P_{j}^{mem}$

$\forall j \sum_{i=1}^{n} y_{ij} V M_{i}^{bw} \leq P_{j}^{bw}$

(1)

The purpose of this model is to find a host machine that has the maximum amount of available resources. The first constraint given under equation (1) determines that each virtual machine is assigned placed to only one machine. The second, third and fourth constraints given under equation (1), check that existing and available resources, including CPU, memory, and bandwidth of jth physical machine that have been chosen for placement of ith virtual machine, have the resources they need a virtual machine or not. If all constraints are satisfied, the virtual machine will be placed on the desired physical machine.
3.2 Task Scheduling

The following optimization model presented in equation 2 is used for scheduling tasks.

\[
\text{Minimize} \quad \frac{\text{Response Time}}{u_1D456} \\quad \forall \sum_{j=1}^{m} T_{ij} = 1 \\
\text{s.t.} \quad F_i \leq A_i + D_i \\
\text{et}_{ij} + D_i \leq c_{t_{ij}}
\]

(2)

We aim to minimize the response time as the objective function of this model. This model includes \(T_{ij}, F_i, A_i, D_i, c_{t_{ij}}\) variables corresponding to the ith task on jth virtual machine, expected finish time of ith task, arrival time of ith task, deadline time of ith task, execution time and completion time of ith task on jth virtual machine. The first constraint given under equation (2) dictates that each task must be assigned to only one virtual machine, the second constraint checks the deadline for execution and termination of ith job, and the last constraint considers that the time to complete ith job on the jth machine is less than the time taken to execute it, taking into account the deadline. To estimation of runtime and completion of work is obtained from the following equation (3) and (4), respectively

\[\text{et}_{ij} = \text{job length} / \text{Mips of VM}_j \times \text{Number of processor}\]  

(3)

\[\text{ct}_{ij} = \text{et}_{ij} + \text{wt}_{i}\]  

(4)

3.3 Load Status

Before scheduling and task assignment to the desired machine, we first evaluate the virtual machine’s workload status based on the load. The load of a machine is determined by parameters including processor load (f1), available memory(f2), bandwidth (f3), which determine the load and state of the machine.

\[F = \{f1, f2, f3\}\]

\[f1 = \text{cpu usage of VM}_i / P_{cp}\]

\[f2 = \text{memory usage of VM}_i / P_{mem}\]

\[f3 = \text{bandwidth usage of VM}_i / P_{bw}\]  

(5)

Defining \(L_i(t) = \sum_{j=1}^{n} i j\) the load degree of a machine can be as follows: The values of \(L_i^{max}(t)\) and \(L_i^{min}(t)\) determine the maximum and minimum load of i-th host, which maximum is 70%, and final decision to choose based on the load status. To choose and allocate resources, their load status must be taken into account to perform the scheduling task. The symbols used in this paper are listed in Table 1.

3.4 Optimization of the Proposed Model

The hill-climbing algorithm is used to optimize models and find the optimal solution for allocating resources to virtual machines and scheduling tasks. This algorithm, which is one of the local search algorithms in the category of incomplete methods for solving optimization problems, means that it may not guarantee correct answers for all input values. Using this algorithm, we look for the optimal solution to the problem.

3.4.1 Hill Climbing Algorithm

An algorithm that is used to find the best answer to a problem or to find the answer that is good enough and optimal. Here are some problems that have several equally valuable answers and we aim to find one of them. To reviews the hill-climbing algorithm, consider the following problem: The hill climbing algorithm is a simple looping that increments direction continuously and one of the simplest ways to implement a heuristic search. This heuristic has the advantages of two Depth-First Search and Breadth-First Search algorithms. We assume that the function F assigns to each member of a finite set s an integer value, and our goal is to find the member of S that is assigned the largest or the smallest value. We also assume that there are multiple F for different
The meaning of the symbols

| Symbol                  | The meaning of the symbols                                      |
|-------------------------|-----------------------------------------------------------------|
| $P_i$                   | The ith physical machine (host)                                 |
| $VM_i$                  | The ith virtual machine (vm)                                    |
| $T_i$                   | The ith task                                                     |
| $F_i$                   | The expected finish time of ith task                            |
| $A_i$                   | The arrival time of ith task                                    |
| $et_{ij}$               | The execution time of ith task on jth virtual machine           |
| $ct_{ij}$               | The completion time of ith task on jth virtual machine          |
| $D_i$                   | The deadline time of ith task                                   |
| $y_{ij}$                | The ith virtual machine on jth host                             |
| $T_{ij}$                | The ith task on jth virtual machine                             |
| $ET$                    | The execution time matrix                                       |
| $CT$                    | The completion time matrix                                      |
| $ET = (et_{ij})_{mn}$   | $CT = (ct_{ij})_{mn}$                                           |

**TABLE 1** The summary of symbols used in the paper

members of $S$ and our goal is to find only one of them. In this algorithm loop executes until the best solution is found for problems. Pseudo-code for this algorithm is as follows:

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**Algorithm 1 Function HILL-CLIMBING returns a solution state**

1: **procedure** HILLCLIMBING(Problem)                         $\triangleright$ The Current and Next are node(variable)
2:  $\text{Current} \leftarrow \text{Make - Node}(\text{INITIAL - STATE}[\text{Problem}])$
3:  **while** true **do**
4:    $\text{Next} \leftarrow \text{highest - valued successor of Current}$
5:    **if** $Value[\text{Next}] \leq Value[\text{Current}]$ **then**
6:      $\text{Current} \leftarrow \text{Next}$
7:  **end if**
8: **end while**
9: **end procedure**

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3.5 Proposed Resource Allocation and Task Scheduling Algorithms

The proposed resource allocation and scheduling are explained as follows:

3.5.1 Resource Allocation to Virtual Machines

For resource allocation dynamically to virtual machines, we select a host with the maximum available resources that satisfies the constraints of the model in equation (1). The status of the host machine should be checked before allocating the host machine for the target virtual machine. If the evaluated machine has sufficient resources, we select the mentioned machine and its resources are allocated to the target virtual machines. Otherwise, the search to find the right machine will continue.

3.5.2 Task Scheduling

After allocating system resources to virtual machines, we need to call a process to balance the load and schedule the jobs. The following steps are performed for task scheduling:
- User requests are sent to the cloud server. The running time and completion of tasks on different machines are estimated and stored in two execution time (ET) and completion time (CT) matrices that used for decision making and machine selection.

- From the set of received requests, we select the one with the least deadline.

- We choose a virtual machine to process the accepted request according to the values in the ET, CT matrices and the constraints of the model.

- The load status and situation of the selected machine, \( L_i(t) \) are evaluated.

- If the load status of the machine is not normal, the search will continue to find the appropriate node.

We repeat the above mentioned steps for remaining and new requests. The pseudo-code of the proposed task scheduling algorithm is as follows:

**Algorithm 2** The proposed algorithm for task scheduling

\[
\text{for } i = 1 \text{ to } M \text{ do (} M \text{ is the total number of jobs)} \\
\text{for } j = 1 \text{ to } N \text{ do (} N \text{ is the number of virtual machines)} \\
\quad \text{Compute } et_{ij} \text{ (equation 3)} \\
\quad \text{Compute } ct_{ij} \text{ (equation 4)} \\
\text{end for} \\
\text{end for} \\
\text{repeat} \\
\quad \text{Selected-Task } = \text{ ith task with minimum deadline} \quad \triangleright \text{ according hill climbing algorithm} \\
\quad \text{for } j = 1 \text{ to } N \text{ do} \\
\quad\quad \text{ } Vm_j = \text{ jth virtual machine with minimum execution time} \\
\quad\quad \text{constraints} (F_i \leq A_i + D_i, et_{j} + D_i \leq ct_j) \quad \triangleright \text{ considering model} \\
\quad \text{end for} \\
\quad \text{Load Degree} Vm_j \leftarrow \text{ Load } - \text{ Degree} (Vm_j) \\
\quad \text{if } \text{Load } - \text{ Degree} (Vm_j) \text{ == normal } \mid \text{idle then} \\
\quad\quad \text{Assign Task}_{i} \text{ to } Vm_j \\
\quad\quad \text{Delete Task}_{i} \text{ from Unscheduled-Tasks} \\
\quad\quad \text{Update CT and ET matrices} \\
\quad \text{end if} \\
\text{until Unscheduled } - \text{Tasks } \neq \text{empty} \\
\]

## 4 Evaluation

This section provides a summary of the steps, implementation tools, and assessments to evaluate the proposed algorithm. We briefly discuss how to implement the proposed algorithm and the simulation steps. We compare the proposed algorithm with FIFO, RoundRobin, MET, MaxMin, MinMin and Genetic Algorithm (GA), implemented with Java in Netbeans IDE using the CloudSim framework. We generate the user requests randomly with the length of (between 1000-5000 Million Instructions (MI)) by using a subroutine. We use a system with intel core i5 2.6 GHz CPU and 6 GB of RAM.

In this section, we compare the results of different simulation scenarios. We have changed the number of queries from 100 to 10,000 and the results for the algorithms are given below. To evaluate the proposed algorithm and compare it with the mentioned algorithms, the characteristics of physical and virtual machines in the cloud considered for simulation are presented in Table 2.

The specifications of Cloudlets that are equivalent to user requests are as presented in Table 3.

Information on simulation scenarios, including the number of jobs, host machines, and virtual machines used in the data center simulation is given in Table 4.
Table 2: Specification of hosts and virtual machines used for simulation

|          | Host | VM  |
|----------|------|-----|
| Bandwidth (Mbps) | 10000 | 1000 |
| Storage (MB)   | 1000000 | 1000 |
| Ram (MB)       | 4096   | 512  |

Table 3: The specification of Cloudlets used for evaluation

| Deadline (m-sec) | Output Size (Byte) | Input Size (Byte) | Cloudlet size (MB) | Processing unit |
|------------------|--------------------|-------------------|--------------------|-----------------|
| 1 - 5            | 400                | 300               | 1000 – 5000        | 1-2             |

Table 4: Information on different simulation scenarios used for evaluation

| No. Simulation | No. jobs | No. VMs | No. host | No. DC |
|----------------|----------|---------|----------|--------|
| 1              | 100      | 2       | 1        | 1      |
| 2              | 200      | 4       | 1        | 1      |
| 3              | 400      | 10      | 4        | 1      |
| 4              | 500      | 50      | 10       | 1      |
| 5              | 3000     | 75      | 10       | 1      |
| 6              | 5000     | 75      | 10       | 1      |
| 7              | 5000     | 100     | 10       | 1      |
| 8              | 10000    | 200     | 20       | 2      |

We use response time, turnaround time, throughput, simulation time, and distribution diagrams between different machines as the comparison metrics. The tables and graphs obtained from the simulation results are explained for each case as follows:

4.0.1 Average response time

Table 5 shows the mean response time for each evaluated algorithms in different simulation scenarios. The comparison of average response time values shows improvement as presented in Figure 1.

| Scenario No. | Proposed Algorithm | FIFO | MET | Round-Robin | Max-Min | Min-Min | GA  |
|--------------|--------------------|------|-----|-------------|---------|---------|-----|
| 1            | 517.497            | 521.659 | 526.417 | 526.417 | 510.816 | 520.133 | 525.911 |
| 2            | 557.962            | 557.134 | 559.503 | 559.503 | 704.189 | 704.189 | 556.068 |
| 3            | 479.417            | 478.394 | 480.028 | 480.028 | 719.888 | 718.360 | 479.360 |
| 4            | 116.12             | 116.450 | 116.688 | 166.688 | 466.075 | 466.075 | 274.659 |
| 5            | 460.314            | 460.093 | 406.259 | 460.259 | 2678.460 | 2678.460 | 1643.701 |
| 6            | 766.698            | 766.544 | 766.710 | 766.710 | 4458.861 | 4458.861 | 3127.343 |
| 7            | 564.959            | 721.157 | 721.316 | 721.361 | 4439.160 | 4439.160 | 2700.113 |
| 8            | 564.782            | 755.435 | 721.316 | 758.262 | 4454.949 | 4454.949 | 2740.269 |

Table 5: Average response time
FIGURE 1 Average response time of the Proposed algorithm compared with FIFO, RoundRobin, MET, Min-Min, Max-Min and GA

4.0.2 Average turnaround time

The evaluation results presented in Table 6 show an improvement in turnaround metric, as shown in Figure 2.

| Scenario No. | Proposed Algorithm | FIFO | MET | Round-Robin | Max-Min | Min-Min | GA |
|--------------|--------------------|------|-----|-------------|--------|--------|----|
| 1            | 517.597            | 521.759 | 526.517 | 526.517 | 510.916 | 520.233 | 526.011 |
| 2            | 558.063            | 557.235 | 559.603 | 559.603 | 704.289 | 704.289 | 556.168 |
| 3            | 479.517            | 479.034 | 480.128 | 480.128 | 719.987 | 718.460 | 479.460 |
| 4            | 116.221            | 116.550 | 116.788 | 116.788 | 466.175 | 466.175 | 274.759 |
| 5            | 460.414            | 460.193 | 460.359 | 460.359 | 2678.560 | 2678.560 | 1643.801 |
| 6            | 766.798            | 766.644 | 766.810 | 766.810 | 4458.961 | 4458.961 | 3127.443 |
| 7            | 565.059            | 721.257 | 721.416 | 721.516 | 4439.260 | 4439.260 | 270.213 |
| 8            | 564.932            | 755.635 | 721.416 | 758.462 | 4455.149 | 4455.149 | 2740.369 |

TABLE 6 Average turnaround time of the simulations

FIGURE 2 Average turnaround time of the simulations
The results and diagrams of average response time show that in scenarios with the high number of requests, data centers, and resources available in data centers (physical and virtual machines), the proposed algorithm has better average response time and turnaround time. Improved response time means improve system utilization and efficiency, waiting time, quality of service and throughput. The improvement of response time and turnaround time based on percentages are given in Table 7.

| Scenario No. | FIFO | MET | Round-Robin | Max-Min | Min-Min | GA |
|--------------|------|-----|-------------|---------|---------|----|
| 1            | 0.79 | 1.69| 1.69        | 0.50    | -1.30   | 1.59|
| 2            | -0.14| 0.27| 0.27        | 20.76   | 20.76   | -0.34|
| 3            | -0.21| 0.12| 0.12        | 33.26   | 33.40   | -0.01|
| 4            | 0.28 | 0.48| 30.33       | 75.08   | 75.08   | 57.72|
| 5            | -0.04| -13.30| -0.01      | 82.81   | 82.81   | 71.99|
| 6            | -0.02| 0.001| 0.001      | 82.80   | 82.80   | 75.48|
| 7            | 21.65| 21.67| 21.68       | 87.27   | 87.27   | 79.07|
| 8            | 25.23| 21.70| 25.51       | 87.32   | 87.32   | 79.38|

**TABLE 7** Percent improvement in response time and turnaround time proposed algorithm to other algorithms

The results show that the higher the number of cloud processing nodes and user requests, the proposed algorithm performs better scheduling and resource allocation. The response time and turnaround time indices have improved dramatically due to the proper allocation of resources and the correct selection of processing nodes to process requests. Besides, we will see that applications are distributed almost evenly among virtual machines, which is the main goal in load balancing.

### 4.0.3 Simulation time

Table 8 shows the simulation time of the different scenarios for evaluated algorithms. As the number of machines and requests increases, the proposed algorithm increases the calculation and searching time to estimate the task execution time which is one of the weaknesses of the algorithm. The results of the simulation time are given in all scenarios as shown in Figure 3.

| Scenario No. | Proposed Algorithm | FIFO | MET | Round-Robin | Max-Min | Min-Min | GA |
|--------------|---------------------|------|-----|-------------|---------|---------|----|
| 1            | 0                   | 0    | 0   | 0           | 1       | 0       | 0  |
| 2            | 0                   | 0    | 0   | 0           | 0       | 0       | 0  |
| 3            | 1                   | 0    | 1   | 1           | 1       | 1       | 1  |
| 4            | 1                   | 1    | 1   | 1           | 1       | 1       | 1  |
| 5            | 13                  | 4    | 5   | 4           | 89      | 70      | 14 |
| 6            | 21                  | 10   | 11  | 9           | 474     | 462     | 45 |
| 7            | 20                  | 10   | 10  | 8           | 460     | 452     | 43 |
| 8            | 41                  | 17   | 10  | 18          | 474     | 526     | 55 |

**TABLE 8** Algorithm simulation time in (sec)

### 4.0.4 Throughput

Table 9 presents the evaluation results for the throughput metric. We define the throughput as the number of tasks done per unit time. These results are shown in Figure 4. The results indicate that the proposed algorithm is more efficient and more jobs can be processed.
| Scenario No. | Proposed Algorithm | FIFO      | MET       | Round-Robin | Max-Min   | Min-Min   | GA        |
|-------------|--------------------|-----------|-----------|-------------|-----------|-----------|-----------|
| 1           | 0.1308609340       | 0.12807048999 | 0.12807048999 | 0.12807048999 | 0.15078180365 | 0.1308609340 | 0.1263567556 |
| 2           | 0.2506485531       | 0.2506485531 | 0.2506485531 | 0.2506485531 | 0.2003606491 | 0.2003606491 | 0.2538393197 |
| 3           | 0.5582927407       | 0.5582849486 | 0.5582849486 | 0.5582849486 | 0.40260890570 | 0.40260890570 | 0.5742670916 |
| 4           | 5.014039310        | 5.015045135 | 5.015045135 | 5.015045135 | 0.5013989029 | 0.5013989029 | 1.3435442697 |
| 5           | 30.525030525       | 30.525030525 | 30.525030525 | 30.525030525 | 30.16894609  | 30.16894609  | 1.3801796993 |
| 6           | 5.000400032        | 5.000400032 | 5.000400032 | 5.000400032 | 0.5096065939 | 0.5096065939 | 1.1467337582 |
| 7           | 5.000750112        | 5.000450040 | 5.000450040 | 5.0013503645 | 0.5101910665 | 0.5101910665 | 1.4467048403 |
| 8           | 10.00050002        | 10.00020000 | 5.000450040 | 10.004001600 | 1.015675942  | 1.015675942  | 1.3831449950 |

**TABLE 9** Values of throughput metric
FIGURE 3 Simulation time of the Proposed algorithm compared with FIFO, RoundRobin, MET, Min-Min, Max-Min and GA

FIGURE 4 Values of throughput metric for the Proposed algorithm compared with FIFO, Round-Robin, MET, Min-Min, Max-Min and GA

4.0.5 Task Distribution between virtual machines
The diagrams presented in Figure 5 show the distribution of requests between virtual machines in different simulation scenarios. The horizontal axis represents the virtual machine identifier and the vertical axis the number of tasks that have been processed by that virtual machine. The results show that as the requests and resources increase, scheduling of tasks is performed almost uniformly due to the intelligent selection of the nodes, which is one of the positive features of the proposed algorithm.

5 CONCLUSION
In this paper, we proposed a dynamic and efficient optimization-based load balancing for big data processing in the cloud. Big data processing requires real-time or near-real-time processing that requires proper resource allocation and scheduling of tasks. We modeled the resource allocation and scheduling based on two optimization models and used the hill-climbing algorithm to find the optimal solution. To schedule the jobs, we estimated the execution time of the requests taking into account the status of loaded machines and found the best virtual machines for processing different tasks. The results obtained from different simulation scenarios show that the proposed algorithm outperforms FIFO, Round-Robin, MET, Min-Min, Max-Min and Genetic algorithm, in response time and turnaround time metrics by 25.23%, 25.52%, 21.70%, 87.32%, 87.32% and 79.38% respectively. Besides,
in our proposed algorithm, a machine always selects to process requests with less workload than other machines, therefore, the distribution of requests between different processing nodes remains almost uniform causing better performance on throughput metric. We also considered a deadline in the optimization model for scheduling and executing tasks that distinguish the proposed algorithm from existing ones. These features make the proposed algorithm highly efficient for near real-time processing in big data applications.

References

1. Klous S, Wielaard N. We are big data: the future of the information society. Springer. 2016.
2. Skourletopoulos G, Mavromoustakis CX, Mastorakis G, et al. Big data and cloud computing: a survey of the state-of-the-art and research challenges. In: Springer. 2017 (pp. 23–41).
3. Zhang R. The impacts of cloud computing architecture on cloud service performance. Journal of Computer Information Systems 2018: 1–9.
4. Chang WL, Laszewski G. NIST Big Data Interoperability Framework: Volume 8, Reference Architecture Interfaces. In: ; 2019.
5. Khan S, Shakil KA, Alam M. Big Data Computing Using Cloud-Based Technologies, Challenges and Future Perspectives. arXiv preprint arXiv:1712.05233 2017.
6. Wang L, Jones R. Big Data Analytics in Cyber Security: Network Traffic and Attacks. Journal of Computer Information Systems 2020; 0(0): 1-8. doi: 10.1080/08874417.2019.1688731
7. Neves P, Schmerl B, Cámara J, Bernardino J. Big Data in Cloud Computing: Features and Issues. In: ; 2016: 307–314.
8. Xiong H, Wang Y, Li W, Chen CM. Flexible, efficient, and secure access delegation in cloud computing. ACM Transactions on Management Information Systems (TMIS) 2019; 10(1): 1–20.
9. Yadav VK, Yadav MP, Yadav DK. Reliable task allocation in heterogeneous distributed system with random node failure: Load sharing approach. In: IEEE. ; 2012: 187–192.
10. Patel N, Chauhan S. A survey on load balancing and scheduling in cloud computing. International Journal for Scientific Research and Development 2015; 1: 185–189.
11. Singh A, Juneja D, Malhotra M. Autonomous agent based load balancing algorithm in cloud computing. Procedia Computer Science 2015; 45: 832–841.
12. Mata-Toledo R, Gupta P. Green data center: how green can we perform. Journal of Technology Research, Academic and Business Research Institute 2010; 2(1): 1–8.
13. Chen Y, Argentinis JE, Weber G. IBM Watson: how cognitive computing can be applied to big data challenges in life sciences research. Clinical therapeutics 2016; 38(4): 688–701.
14. Shah N, Farik M. Static load balancing algorithms in cloud computing: Challenges & solutions. International Journal Of Scientific & Technology Research 2015; 4(10): 365–367.
15. Fox G, Qiu J, Jha S, Ekanayake S, Kamburugamuve S. Big data, simulations and hpc convergence. In: Springer. 2015 (pp. 3–17).
16. Lohr S. The age of big data. New York Times 2012; 11(2012).
17. Kansal NJ, Chana I. Cloud load balancing techniques: A step towards green computing. IJCSI International Journal of Computer Science Issues 2012; 9(1): 238–246.
18. Baliga J, Ayre RW, Hinton K, Tucker RS. Green cloud computing: Balancing energy in processing, storage, and transport. Proceedings of the IEEE 2010; 99(1): 149–167.
19. Hwang K, Dongarra J, Fox GC. Distributed and cloud computing: from parallel processing to the internet of things. Morgan Kaufmann. 2013.

20. Ghomi EJ, Rahmani AM, Qader NN. Load-balancing algorithms in cloud computing: A survey. Journal of Network and Computer Applications 2017; 88: 50–71.

21. Rastogi G, Sushil R. Analytical literature survey on existing load balancing schemes in cloud computing. In: IEEE. 2015: 1506–1510.

22. Wang SC, Yan KQ, Liao WP, Wang SS. Towards a load balancing in a three-level cloud computing network. In: 1. IEEE. 2010: 108–113.

23. Mirtaheri SL, Grandinetti L. Dynamic load balancing in distributed exascale computing systems. Cluster Computing 2017; 20(4): 3677–3689.

24. Kumar M, Sharma S. Dynamic load balancing algorithm for balancing the workload among virtual machine in cloud computing. Procedia computer science 2017; 115: 322–329.

25. Karthick A, Ramaraj E, Subramanian RG. An efficient multi queue job scheduling for cloud computing. In: IEEE. 2014: 164–166.

26. Kaur S, Kaur G. A Review of Load Balancing Strategies for Distributed Systems. International Journal of Computer Applications 2015; 121(18).

27. Mell P, Grance T, others. The NIST definition of cloud computing. In: Computer Security Division, Information Technology Laboratory. 2011.

28. Sharma G. A review on different approaches for load balancing in computational grid. Journal of Global Research in Computer Science 2013; 4(4): 82–85.

29. Liu G, Li J, Xu J. An improved min-min algorithm in cloud computing. In: Springer. 2013: 47–52.

30. El-Zoghdy S, Ghoniemy S. A survey of load balancing in high-performance distributed computing systems. International Journal of Advanced Computing Research 2014; 1.

31. Elzeki O, Reshad M, Elsoud M. Improved max-min algorithm in cloud computing. International Journal of Computer Applications 2012; 50(12).

32. Li X, Mao Y, Xiao X, Zhuang Y. An improved max-min task-scheduling algorithm for elastic cloud. In: IEEE. 2014: 340–343.

33. Li J, Ma T, Tang M, Shen W, Jin Y. Improved FIFO scheduling algorithm based on fuzzy clustering in cloud computing. Information 2017; 8(1): 25.

34. Hamdani M, Aklouf Y, Bouarara HA. Improved fuzzy Load-Balancing Algorithm for Cloud Computing System. Proceedings of the 9th International Conference on Information Systems and Technologies 2019: 1–4.

35. Daraghmi EY, Yuan SM. A small world based overlay network for improving dynamic load-balancing. Journal of Systems and Software 2015; 107: 187–203.

36. Saleh H, Nashaat H, Saber W, Harb HM. IPSO task scheduling algorithm for large scale data in cloud computing environment. IEEE Access 2018; 7: 5412–5420.

37. Sanaj M, Prathap PJ. Nature inspired chaotic squirrel search algorithm (CSSA) for multi objective task scheduling in an IAAS cloud computing atmosphere. Engineering Science and Technology, an International Journal 2019.

38. Samadi Y, Zbakh M. Threshold-based load balancing algorithm for Big Data on a Cloud environment. In: ACM. 2017: 18.

39. Manikandan N, Pravin A. LGSA: Hybrid Task Scheduling in Multi Objective Functionality in Cloud Computing Environment. 3D Research 2019; 10(2): 12.
40. Mousavi S, Mosavi A, Varkonyi-Koczy AR. A load balancing algorithm for resource allocation in cloud computing. In: Springer.; 2017: 289–296.

41. Vashisht V, Chhabra A, Sood A. A predictive approach to task scheduling for Big Data in cloud environments using classification algorithms. In: IEEE.; 2017: 188–192.

42. Lagwal M, Bhardwaj N. Load balancing in cloud computing using genetic algorithm. In: IEEE.; 2017: 560–565.

43. Semmoud A, Hakem M, Benmammar B, Charr JC. Load balancing in cloud computing environments based on adaptive starvation threshold. Concurrency and Computation: Practice and Experience 2020; 32.

44. Tadi AA, Khayyambashi MR, Farsani HK. OASM: An overload-aware workload scheduling method for cloud computing based on biogeographical optimization. Int. J. Netw. Manag. 2020; 30.
FIGURE 5 Distribution of tasks in Scenarios 1 to 8 between virtual machines
