A Multi-Class Task Scheduling Strategy for Heterogeneous Distributed Computing Systems

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Received November 13, 2015; accepted October 12, 2015; published January 31, 2016

Abstract

Performance enhancement is one of the most important issues in high performance distributed computing systems. In such computing systems, online users submit their jobs anytime and anywhere to a set of dynamic resources. Jobs arrival and processes execution times are stochastic. The performance of a distributed computing system can be improved by using an effective load balancing strategy to redistribute the user tasks among computing resources for efficient utilization. This paper presents a multi-class load balancing strategy that balances different classes of user tasks on multiple heterogeneous computing nodes to minimize the per-class mean response time. For a wide range of system parameters, the performance of the proposed multi-class load balancing strategy is compared with that of the random distribution load balancing, and uniform distribution load balancing strategies using simulation. The results show that, the proposed strategy outperforms the other two studied strategies in terms of average task response time, and average computing nodes utilization.

Keywords: Resource Management; Load Balancing; Distributed Computing; Queuing Theory.

http://dx.doi.org/10.3837/tiis.2016.01.007 **ISSN : 1976-7277**

1. Introduction

Recently, many scientific problems become very complex and complicated. These problems require huge computing power and storage space. Most of the previous used technologies such as traditional parallel/ distributed computing systems become unsuitable for solving such problems. At the same time, the availability of low-cost powerful computers and high-speed networks are changing rapidly that leads nowadays to almost all computers are connected to the Internet. The networked computers form a (cluster of workstations) or a distributed system. This technology advances enhanced the possibility of using geographically distributed and multi-owner resources to solve large-scale problems in many fields such as science, engineering, and commerce.

As a result, new computing paradigms such as Cluster, Grid, and Cloud computing have been emerged [1-3, 14]. These newly emerged computing environments are referred to as High Performance Distributed Computing Systems (HPDCS). These Computing environments provide dependable, consistent, pervasive, and inexpensive access to high-end computational capabilities such as computers, storage space, software applications, and data. They support the sharing and coordinated use of resources independently of their type and location in dynamic virtual organizations (VOs) consisting of individuals, institutions, and resources solving computationally intensive applications. Also, these computing systems use common interface to link computing clusters or LANs together.

Many users or VOs can share these clusters and through a local resource management system, each cluster or LAN applies a local policy that defines their access rights. The primary motivation of these newly emerged computing systems is to provide users and applications with pervasive and seamless access to vast high performance computing resources by creating an illusion of a single system image. Thus HPDCS are designed so that users won't have to worry about where computations of their tasks are being performed [1-3,5-8,11,13-19].

The HPDCS offer a variety of services such as computation services, application services, data services, information services, and knowledge services. These services are provided by the servers or processing elements in the computing system. The servers and the processing elements are typically heterogeneous in the sense that they have different processor speeds, memory capacities, and I/O bandwidths [1-3,7,14-19,21-29].

In such computing systems, online users submit their jobs anytime and anywhere to a set of dynamic resources. Jobs arrival and processes execution times are stochastic. The heterogeneity of the available resources coupled with the uneven job arrival patterns, and stochastic distribution of job processes execution times may lead to a situation where some computing nodes become heavily loaded while others in a different site may be lightly loaded or even idle.

It is therefore desirable to transfer some jobs from the heavily loaded servers to the idle or lightly loaded ones aiming to efficiently utilize the available computing resources. The process of load redistribution is known as load balancing. To achieve the promising potentials of tremendous distributed computing resources, efficient and effective load balancing and resource management algorithms should be utilized [1-10].

Load balancing algorithms can be classified into static or dynamic [4,8,9,40]. In static load balancing policies, the load balancing decisions are made deterministically or probabilistically at compile time and remain constant during runtime. They are not affected by the runtime system state. In contrast, dynamic load balancing policies attempt to use the runtime system

state information to make more informative load balancing decision, see [4,8,9,10,11,40] for more details.

A number of load balancing algorithms for traditional parallel and distributed systems have been developed [4,9,12,20,40]. Unfortunately, these load balancing algorithms cannot work directly in recent distributed computing environments such as Cluster, Grid, and Cloud computing systems. Therefore, it is essential to consider the impact of various dynamic characteristics of the HPDCS in designing and analyzing the load balancing algorithms [1-3,14,29] for such computing systems..

Recently, many papers have been published to address the problem of load balancing in HPDCS [14,15-18,41]. Almost all of these papers considered jobs as one class. They ignored the fact that distributed system's jobs varies widely by their nature. These jobs range from batch processes and CPU-bounded jobs to real time and even traditional jobs. For each job it is required to satisfy the associated performance and quality of service constraints. Hence, it is therefore important to classify these jobs into different classes aiming to utilize the system resources effectively and at the same time satisfies the users demands. Only a little number of researchers dealt with the multi-class of jobs load balancing problem in HPDCS such as [12, 19,20].

In this paper, we propose a load balancing strategy for multiclass jobs that could be used in the HPDCS. The proposed load balancing strategy takes into account the heterogeneity of the system's computational resources as well as the task heterogeneity. The performance of the proposed load balancing strategy is evaluated and compared with two other load balancing strategies by simulation. The simulation results show that the performance of the proposed load balancing strategy outperforms the other studied strategies in terms of average job response time, and average computing node utilization.

The rest of this paper is organized as follows: Section II presents related work. Section III describes the studied model and assumptions. Section IV introduces the proposed multi-class load balancing strategy. Section V presents the simulation results and discussion. Finally, Section VI summarizes this paper.

2. Related Work

HPDCS consist of a dynamic set of heterogeneous resources communicating via one or more communication networks. Users of these systems submit their tasks at anytime and anywhere. One of the most important problems in the HPDCS is balancing the system workloads among computing nodes aiming to efficiently utilize available resources and hence improve system performance [14,19,29]. A large number of researchers studied the load balancing problem in the traditional parallel and distributed systems. They developed a number of load balancing algorithms such as [4,9,10,20,37,40]. Unfortunately, these algorithms cannot work directly in the recent HPDCS because they do not consider the dynamic characteristics and the heterogeneity of these systems in designing and analyzing the load balancing algorithms. Some of these load balancing algorithms have been modified to be able to deal with the HPDCS, and other completely new load balancing algorithms for such computing systems have been developed.

In [17], the authors proposed a simple and efficient load balancing algorithm that balances the system workloads between computing clusters that are far apart from each other. In [29,39], the authors presented a general survey of job scheduling and resource management strategies in grid computing environment. Also in [30, 31], the authors presented a static load balancing algorithm in a heterogeneous system with servers and computing nodes where servers balance

load among all computing nodes in a round robin fashion. Their algorithm requires each server to have the workload information of the status for all computing nodes as well as the load allocated by all other servers. The authors in [32] presented load balancing strategy for a heterogeneous distributed computing system environment in which the scheduler selects computational resources based on the task characteristics, task requirements, and resource's information. The aim of their strategy was to minimize the Total Time to Release (TTR) for the individual task. TTR includes processing time of the task, waiting time in the queue, transfer of input and output data to and from the resource. The load balancing algorithms presented in [33] introduce a job migration strategy that balances the system workload when any of the computing nodes becomes overloaded, but they does not consider the system resource and network heterogeneity.

In [34], the authors proposed a ring topology for the Grid computing managers. The Grid managers are responsible for managing a dynamic pool of computing nodes. They proposed a load balancing algorithm based on the real computing nodes workload information. Unfortunately, it is not applicable because of its huge overhead cost in collecting the computing nodes workload information specially for large scale systems. The authors in [1,3,22,25,34-36] introduced many hierarchical load balancing algorithms for heterogeneous distributed computing systems. These algorithms are implemented at various levels to reduce the communication overhead and hence minimize the mean response time of the system's application.

In [22], load balancing strategies are proposed for a 2-level hierarchy grid computing model. The authors evaluated the performance of these strategies at the global scheduler and local scheduler levels. The strategies presented in [11,22] did not have any task allocation procedure and they also did not consider the communication cost between clusters. Their load balancing strategy collects the computing nodes workload information periodically by a central master node called Grid Manager. This is a centralized policy and it suffers from the central point of failure problem as the failure of the Grid Manager leads to the whole system failure.

In [3] a two-level load balancing strategy is presented. It takes into account the heterogeneity of the distributed system computing resources. This strategy balances the system's workload based on the processing capacity of the computing nodes. It overcomes the bottleneck of the strategies presented in [11,22,25]. It removes the Grid Manager node which centralizes the system global load information. In [35], the same authors of [34] presented Grid managers hierarchical structure which improves scalability of the grid computing environment. Their load balancing strategy has task allocation policy which regulates automatically the job flow rate directed to a given grid manager. In [15], the authors presented a two levels task scheduling strategy which balances the workload in cloud computing. It takes into account the new features of cloud computing, such as virtualization and flexibility etc. In [16,17], comparative studies between some of the existing cloud computing load balancing algorithms are conducted.

All the previously discussed strategies deal with the user tasks as one class which is against the reality as the tasks differ in many aspects by nature. Some tasks may be I/O-Bounded, CPU-Bounded, and others may be interactive. Hence, it is not fair to deal with all tasks as one class. Only countable number of researchers deals with users tasks as multi-classes. In [12] the authors presented a new metrics to qualify system availability and heterogeneity for multi-class user tasks. In [20,40], the authors studied the problem of scheduling different classes of users tasks in heterogeneous distributed computing systems. They proposed optimal static load balancing policies. Finally, the authors in [19] proposed two dynamic load

balancing schemes for multi-user jobs in heterogeneous distributed systems and compared their performance using simulation. The objectives of the two polices are different. The first one minimizes the whole system average response time, while the other minimizes the average task response time individually. Their performance is compared with another two static load balancing strategies. As usual the dynamic strategies outperforms the static ones in terms of response time for low and moderate communication overhead, and they have the same performance as the static ones if the system communication overhead is high.

In this paper, we propose a multi-class load balancing strategy that balances different classes of non-cooperative user's tasks on multiple heterogeneous distributed computing nodes. The main goal of this strategy is to minimize the per-class mean response time. The scheduler consists of two modules. The first is the availability detecting model that is used to find all computing nodes in the system that satisfy all the requirements of every submitted job from all classes, and group these candidate computing nodes. The second is the load balancing model. It receives the set of candidate computing nodes from the availability detecting model and selects from them the one that gives the minimal response time to execute the user job. The proposed multi-class load balancing strategy takes into account the heterogeneity of the computing nodes. It distributes the system's workload among all the available computing nodes by evenly distributing the service utilization aiming to minimize the response time.

The system average job response time, and the average computing node utilization are considered as the main performance metrics that need to be minimized and maximized respectively. The computing nodes utilize a local priority scheduling policy that gives higher priority to job classes with higher service rates at that computing node.

The proposed strategy provides the following unique characteristics of practical distributed computing environment:

- Heterogeneity: The heterogeneity of system's computing nodes is considered in the proposed strategy.
- Tasks are non-preemptable: The execution of the tasks on any computing node can't be suspended until completion.
- Tasks are totally independent: There is no inter-process communication between tasks.
- Tasks are computation intensive (CPU-bounded): Tasks spend more time doing computations in the CPU than doing I/O operations.

3. Proposed Framework

In this paper, we consider a heterogeneous distributed computing system model in which a set of n Computing Nodes (CNs) are connected via a high speed network as shown in **Fig. 1.** In this network, nodes are numbered 1, 2,...,n, and the system is utilized to process m independent classes of non-cooperative tasks submitted by users. Each computing node in the system consists of a single exponential server with a service rate μ_i (i = 1, 2, ...,n), and its service discipline is first-come-first-served (FCFS), or processor sharing whereby the service rate for each job equals μ_i / n when the number of jobs in the ith node queue is n.

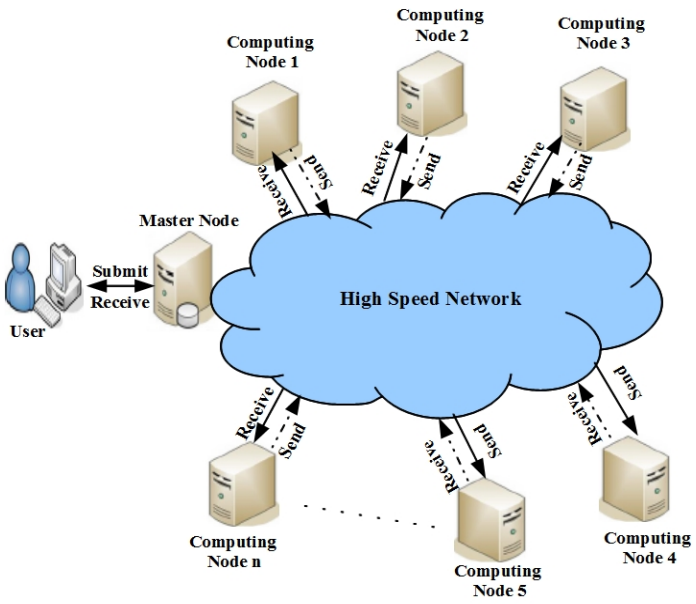

Fig. 1. System architecture

Computing nodes in the system differ in their speeds, memory, and disk space. A master node or a load manager is responsible for balancing system's workload and monitoring available system resources. **Fig. 2** shows the system queueing model. It consists of a task scheduling queue, task scheduler, and n local task queues. The scheduler queue is a temporarily buffer that is large enough to hold all incoming tasks. The FCFS scheduling policy is applied for tasks waiting in schedule queue, and local queues. FCFS ensures certain kind of fairness, does not require advance information about the task execution time, do not require much computational effort, and is easy to implement. The scheduler is composed of two modules namely: Availability Detecting Model (ADM), and Load Balancing Model (LBM). For every task in j^{th} class, the ADM finds all CNs in the system which satisfy the task requirements, and group these CNs in the set A_j. The ADM then passes the set A_j to the LBM to select the computing node from A_j that offers the minimal anticipated response time for executing the task as a candidate computing node. Users can submit tasks form any of the m classes to the system.

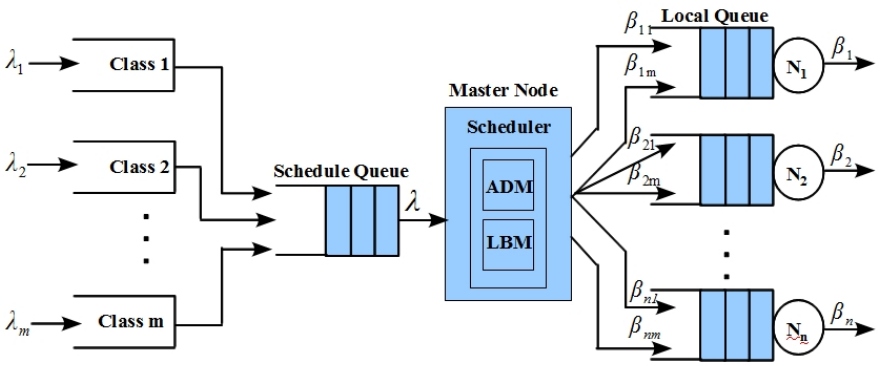

Fig. 2. System queuing model

We assume that the tasks submitted to the system are totally independent tasks with no inter-process communication between them, and that they are computation intensive tasks. Also, we assume that tasks of the j^{th} $(1 \le j \le m)$ class arrive to the system according to ergodic process, such as time-invariant Poisson process, with inter-arrival times which are independent, identically, and exponentially distributed with rate λ_k. Simultaneous arrivals are excluded.

For future reference, the notation that is used throughout this paper is summarized in the following table:

Table 1. Notation Definitions

Notation	Definition
n	Number of computing nodes in the system $(1 \le n \le \infty)$
m	Number of classes of tasks submitted to the system $(1 \le m \le \infty)$
λ_j	jth class task arrival rate to the system
λ	Total system arrival rate from all classes (See Eq. 1).
P_{ij}	The probability that tasks from the jth class are dispatched to the ith computing node.
β_{ij}	Processing rate (load) at ith node from jth class tasks. (See Eq. 2)
β_i	Total processing rate (load) of computing node i. (See Eq. 3)
β	System's total task processing rate (load) for all classes. (See Eq. 4)
μ_{ij}	Allocated service rate at ith node for jth class task's.
μ_i	Total service rate of computing node i (See Eq. 5).
μ	Total system service rate (See Eq. 6).
ρ_{ij}	j^{th} class service utilization at the ith node (See Eq. 7)
ρ_i	ith computing node service utilization (See Eq. 8)
ρ	System service utilization (See Eq. 9).
ρc_j	The system j^{th} class service utilization (See Eq. 10)
TN_i	The i^{th} computing node's mean response time over all classes (See Eq. 11).
TC_j	System expected mean task response time of jth class tasks (See Eq. 12).
T	The system's mean response time (See Eq. 13).

The system total task arrival rate from all classes is denoted by λ and λ_j is the j^{th} class task arrival rate to the system. Hence

$$\lambda = \sum_{j=1}^{m} \lambda_j \tag{1}$$

Denote β_{ij} as the i^{th} computing node processing rate of the j^{th} class tasks, which is also referred to as ith computing node load from the jth class.

Let P_{ij} be the probability that ith computing node receives tasks from the jth class, where i=1,2,…,n, and j=1,2,…,m.

Hence, the ith computing node workload from the jth class is computed by:

$$\beta_{ij} = P_{ij}\lambda_j, \quad i=1,2,?n, \quad \text{and} \quad j=1,2,?m \quad . \tag{2}$$

Hence, the total workload of the i[th] computing node i from all classes can be expressed as

$$\beta_i = \sum_{j=1}^{m} \beta_{ij} = \sum_{j=1}^{m} P_{ij}\lambda_j, \quad i=1,2,?n \quad . \tag{3}$$

As a result, the system's total workload from all classes, β, can be computed as follows:

$$\beta = \sum_{i=1}^{n} \beta_i = \sum_{i=1}^{n}\sum_{j=1}^{m} \beta_{ij} = \sum_{i=1}^{n}\sum_{j=1}^{m} P_{ij}\lambda_j \tag{4}$$

Denote μ_{ij} as the allocated service rate at ith node for jth class task. Hence the corresponding expected service time is computed by $\frac{1}{\mu_{ij}}$. As mentioned earlier, the service times of every computing node has exponential distribution which is independent from the arrival process. Hence the ith computing node service rate can be computed by:

$$\mu_i = \sum_{j=1}^{m} \mu_{ij}, \quad i = 1,2,...,n. \tag{5}$$

Consequently, the total system service rate is computed by:

$$\mu = \sum_{i=1}^{n} \mu_i = \sum_{i=1}^{n}\sum_{j=1}^{m} \mu_{ij} \tag{6}$$

Denote ρ_{ij} as the j[th] class service utilization (traffic intensity) at the i[th] computing node. It is computed by:

$$\rho_{ij} = \frac{\beta_{ij}}{\mu_{ij}} = \frac{P_{ij}\lambda_j}{\mu_{ij}}, \; i = 1,2,...,n, \text{and } j = 1,2,...,m. \tag{7}$$

Hence, the service utilization for all tasks allocated to i[th] computing node is computed by:

$$\rho_i = \sum_{j=1}^{m} \rho_{ij} = \sum_{j=1}^{m} \frac{\beta_{ij}}{\mu_{ij}} = \frac{\beta_i}{\mu_i}, \; i = 1,2,...,n. \tag{8}$$

Consequently, the total system service utilization can be computed by:

$$\rho = \sum_{i=1}^{n} \rho_i = \sum_{i=1}^{n} \sum_{j=1}^{m} \rho_{ij} = \sum_{i=1}^{n} \sum_{j=1}^{m} \frac{\beta_{ij}}{\mu_{ij}} = \sum_{i=1}^{n} \frac{\beta_i}{\mu_i} = \frac{\beta}{\mu} \tag{9}$$

Finally, the total system service utilization of the j[th] class ρc_j can be computed as follows:

$$\rho c_j = \sum_{i=1}^{n} \rho_{ij} = \sum_{i=1}^{n} \frac{\beta_{ij}}{\mu_{ij}} = \frac{\lambda_j}{\sum_{i=1}^{n} \mu_{ij}}, j = 1,2,..,m \tag{10}$$

The stability condition for the studied system model is $\lambda < \mu$, see [38] for more details.
In this research, each node is modeled as a single M/M/1 queue. Thus the mean response time of the i[th] computing node can be computed as follows:

$$TN_i = \frac{(1/\mu_i)}{(1-\rho_i)}, \ i = 1,2,...,n. \tag{11}$$

Hence, the system expected mean response time for the j[th] class tasks can be obtained as follows:

$$TC_j = \sum_{i=1}^{n} P_{ij} TN_i, \ \ j = 1,2,...,m. \tag{12}$$

Form Eq. 12, the average overall system mean response time overall classes can be computed by:

$$T = \sum_{j=1}^{m} \left(\frac{\lambda_j}{\lambda} TC_j \right) = \sum_{j=1}^{m} \left(\frac{\lambda_j}{\lambda} \sum_{i=1}^{n} P_{ij} TN_i \right) \tag{13}$$

From Eq. 13, one can notice that the overall system mean task response time can be minimized by minimizing the mean response time of j[th] class. Hence, the scheduling problem can be expressed as follows:

$$\text{Minimize} \quad TC_j = \sum_{i=1}^{n} P_{ij} TN_i, \ \ j = 1,2,...,m.$$

subject to

$$\sum_{i=1}^{n} \beta_{ij} = \lambda_j, \quad j = 1,2,...,m,$$

$$\beta_{ij} \geq 0, \qquad i = 1,2,...,n, \text{ and } \ j = 1,2,...,m.$$

4. Proposed Multi-Class Load Balancing Strategy

In this section, the strategy of scheduling different classes of tasks on multiple distributed heterogeneous CNs (servers) is presented. The proposed strategy takes into

account the heterogeneity of the system's computational resources. It balances the system's workload among CNs by evenly distributing the service utilization aiming to minimize the average response time. In other words, the system's workload is perfectly balanced between CNs by making all the CNs service utilization equal. This strategy minimizes the per-class mean response times. It has two distinct decisions:

- The tasks allocation to the CNs; and
- The tasks execution order at each computing node.

The first decision is considered as a global load-balancing optimization problem in which the tasks are distributed among the multiple heterogeneous CNs to minimize the mean response-time of each class. The second is a local decision at each computing node and consists of solving an optimal sequencing problem: given a mix of tasks at a computing node, determine the best order of service for the queued tasks to minimize the mean class response time. The proposed scheduling strategy puts the following restrictions on these two decisions:

- Allocation: tasks are allocated to CNs immediately upon arrival in a probabilistic manner; i.e., a task is assigned to a CN based on routing probabilities $\{P_{ij}\}_{1\le i\le n,1\le j\le m}$. the values of the routing probabilities are determined using the scheduling strategy algorithm which minimizes the mean class task response time. This algorithm will be explained later.
- Sequencing: The sequencing strategy is the same at each CN and it is a simple static priority policy. It does not require knowledge of the future, and the execution of a task cannot be interrupted and subsequently resumed (i.e., non-preemptive).

The proposed scheduling strategy utilizes an existing optimal sequencing strategy [20] which minimizes the mean response time of all classes. It is based on proposition 2.1 in [20].

Proposition 1. Given an n-node heterogeneous system, and an m-class M/M/1 queue, class j has arrival rate λ_j and service rate μ_{ij} at node i. The sequencing strategy on node i that gives priority to class j over k whenever $\mu_{ij} \ge \mu_{ik}$ minimizes the system overall mean response time; see Eq. 13.

This proposition can be proved directly from proposition 2.1 in [20].

Proposition 1 indicates that classes with higher service utilization are given high priority in the scheduling process. Using this sequencing strategy, and without loss of generality, the task classes are reordered and labeled such that $\rho c_1 \ge \rho c_2 \ge \ldots \ge \rho c_m$

Where, $\dfrac{\lambda_j}{\sum_{i=1}^{n} \mu_{ij}}$, (j=1,2,…,m) is the system j^{th} class service utilization (See Eq. 10).

This relabeling process assigns a number of priority levels to the task classes. As a result of this sequencing strategy the j^{th} class tasks are assigned priorities higher than the k^{th} class tasks if j<k.

For the allocation strategy, the master node (load manager) allocates arriving tasks to CNs immediately upon arrival in a probabilistic manner; i.e., a task is assigned to a CN based on routing probability $\{P_{ij}\}_{1\le i\le n,1\le j\le m}$. The proposed allocation algorithm determines the

probability that minimizes the response time of all classes. This algorithm selects the CN that minimizes the mean class task response time, and at the same time, it should not be overloaded for computing the task.
To satisfy this, the proposed algorithm uses the following service utilization measure L_i to detect the relative workload of each computing node i:

$$L_i = \frac{\rho_i}{\left(\frac{\rho}{n}\right)},\ i = 1,2,...,n. \tag{14}$$

Where ρ_i is the i[th] computing node service utilization given by Eq. (8), and (ρ/n) is the system's average computing node utilization given by Eq. (9). The proposed scheduling strategy aims to keep L_i very close to 1 which means that the system's CNs service utilization is evenly distributed. I_n the following lines, we list the details of the proposed allocation algorithm:
We assume that the tasks submitted to the system are totally independent tasks with no inter-process communication between them, and that they are computation intensive tasks. The FCFS scheduling policy is applied for tasks waiting in queues, both at schedule queue and Local queues. FCFS ensures certain kind of fairness, does not require advance information about the task execution time, does not require much computational effort, and is easy to implement [2,3].

4.1 Multi-Class Load Balancing Strategy

1. Reorder and label the task classes such that $\rho c_1 \geq \rho c_2 \geq \ldots \geq \rho c_m$, where, $\rho c_j = \frac{\lambda_j}{\sum_{i=1}^{n} \mu_{ij}}$, (j=1,2,…,m) is the system j[th] class service utilization.
2. For each class j do
    a. Set $TC = \infty$; /* as initial value for the class response time */.
    b. Set N_{min}=1, and L_{min}= ∞ ;/* Assume that the lightest CN is node 1 and its relative workload is ∞ */
    c. Create a set of CNs A_j that satisfy the j[th] class tasks software and hardware requirements $(A_j \subseteq n)$.
    d. For each computing node i in A_j do
        i. Set P_{ij}=1;/* assume that the task will be allocated to that computing node, and calculate the expected response time for j[th] class TC_j using Eq. 12 */
        ii. Calculate the relative workload L_i for that node using Eq. 14.
        iii. if ((TC_j<TC) && (L_i<L_{min})) then
            1. TC=TC_j;
            2. L_{min}=L_i;
            3. N_{min}=i;
        iv. End if
    e. End for

f. $P_{N_{\min} j} = 1$; /* that is j^{th} class task will be allocated to N_{min} computing node */

g. Allocate j^{th} class tasks to computing node N_{min};

3. End for

The previously outlined task allocation algorithm aims to minimize the mean response time for multiclass tasks running in a heterogeneous distributed computing systems. In step 1, the algorithm starts by reordering and labeling all the classes in a way that gives higher priorities to classes with higher traffic intensity. This is done by reordering the classes in a way that the following condition; $\frac{\lambda_1}{\sum_{i=1}^{n} \mu_{i1}} \geq \frac{\lambda_2}{\sum_{i=1}^{n} \mu_{i2}} \geq .... \geq \frac{\lambda_m}{\sum_{i=1}^{n} \mu_{im}}$ is satisfied.

For every class *j*, the algorithm sets initial values for the class response time TC, lightest computing node N_{min}, and lowest workload L_{min} in steps 2.a, and 2.b. Then in step 2.c, the algorithm creates a set A_j of CNs that satisfy the class task hardware and software requirements. Step 2.d is the core of the proposed allocation algorithm. It selects the computing node N_{min} in A_j that minimizes the j^{th} class mean response time and has the lightest work load L_{min} by computing the relative workload using Eq. 14. This is done by estimating the j^{th} class expected mean response times and the relative workloads for all CNs in the set A_j using equations 11 and 13 respectively. Step 2.d in the algorithm has three sub-steps. The sub-step 2.d.i assumes that the j^{th} class tasks will be allocated to the i^{th} computing node (i in A_j) by setting P_{ij}=1 and then it computes the j^{th} class expected mean response times on that CN using Eq. 12. After that, in the sub-step 2.d.ii, the algorithm computes the relative workload L_i for the candidate computing node i in A_j using Eq. 14. Finally, in the sub-step 2.d.iii, the algorithm determines the computing node N_{min} in A_j that minimizes j^{th} class tasks mean response time and having the lightest relative workload. Steps 2.f, and 2.g allocate j^{th} class tasks to N_{min} node by setting $P_{N_{\min} j} = 1$ which minimizes the class mean response time.

4.2 Performance Metrics

The performance metrics used to evaluate the proposed strategy in this research are:

1. Average Task Response Time: The length of time between the instant from the task arrival time to the system and the instant when it leaves it, after all processing and communication are over is referred to as the task response time. The average response time of multiple task classes is computed as in Eq. 13.
2. Average Computing Node Utilization: It is the average of the percentage of total node busy time out of total node available time for all computing nodes.

5. Simulation Results and Discussion

5.1 Experimental Environment

In this section, the performance of the proposed multi-class load balancing algorithm is evaluated using simulation. Even though there are many available tools for simulating scheduling algorithms such as network simulator NS2, OmNet++, Arena, Alea, OptorSim, and GridSim, in this study, all the simulation experiments are performed using GridSim v4.0 [25].

It provides facilities for modeling and simulating entities in distributed computing environments such as users, heterogeneous resources, applications, and resource load balancers which are used in designing and evaluating load balancing algorithms. To effectively evaluate the performance of the proposed multi-class load balancing algorithm, a heterogeneous environment for the studied model is built using different resource specifications. In this environment, resources differ in their operating systems, storage, CPU speed, and RAM. Using GridSim, Gridlet objects are used to model user tasks. It has all needed information related to the task's and the execution management details. Also, from the Grid Information Service (GIS) entity, all the needed information about the available system resources can be obtained as it keeps track of all resources available in the simulation environment. A PC (Core I3 Processor, 3.1 GHz, 4GB RAM) running on Windows 7 OS is used to carry out all the simulations experiments.

5.2 Simulation Results and Analysis

Tasks form different classes arrive to the scheduler sequentially with inter-arrival times which are independent, identically, and exponentially distributed. Simultaneous arrivals are excluded. Service times are independent and exponentially distributed. Task parameters (such as size, requirements and service demand) are generated randomly. Each result presented is the average value obtained from 10 simulation runs with different random numbers seeds. In the simulator, collecting statistics starts after ten minutes warm up interval. All time units are in seconds. The performance of the proposed algorithm is evaluated using a wide range of system parameters by varying the system arrival rate λ, system service rate μ and number of computing nodes n.

The performance of a heterogeneous distributed computing system under the proposed multi-class load balancing strategy is compared with two other policies namely; Random Distribution Load Balancing Strategy (RDLBS) and Uniform Distribution Load Balancing Strategy (UDLBS). In the RDLBS a computing node for a task execution is selected randomly without considering any performance metrics to that computing node or to the system in mind. This strategy is explained in [22].

In the UDLBS the tasks flow rate (routing probability) from the scheduler to a computing node is fixed to the value $\frac{1}{n}$, where n is the number of computing nodes in the system. However, in the Proposed Multi-Class Load Balancing Strategy (PMCLBS) all the arriving user tasks from different classes to the scheduler are distributed on the computing nodes that minimize their class response time. Also, the computing nodes utilize a scheduling policy which gives higher priority to classes with higher service rates and this policy minimizes the response time as it is proved in [20].

In the first experiment, we study the effect of varying the system's traffic intensity from 0.1 to 0.9 on the performance of a heterogeneous distributed computing system having 16 computing nodes. **Fig. 3**, shows the system average response time of the three evaluated scheduling strategies. From that figure, one can easily notice that the PMCLBS outperforms the RDLBS and the UDLBS in terms of average response time. The improvement in response time increases as the system traffic intensity increases. This performance was anticipated because the PMCLBS allocates tasks to a computing node which minimizes the class response time, and the computing node in turn utilizes a scheduling policy which gives higher priority to classes with higher service rates. In contrast, the RDLBS randomly selects a computing node

for executing task and the computing node in turn services tasks using pure FCFS scheduling policy. Also, the UDLBS evenly distributes the system workload on the computing nodes without putting any (computing node, or system) performance metrics in mind, and the computing node in turn services tasks using pure FCFS scheduling policy.

Fig. 4, shows the average computing node utilization using the three evaluated scheduling strategies. From that figure, it is clear that as the system traffic intensity increases, the computing nodes utilization increases using the three evaluated scheduling strategies. The utilization of computing nodes is almost the same for low system workloads. The PMCLBS utilizes the computing nodes more efficiently that the RDLBS, and the UDLBS for higher system workloads.

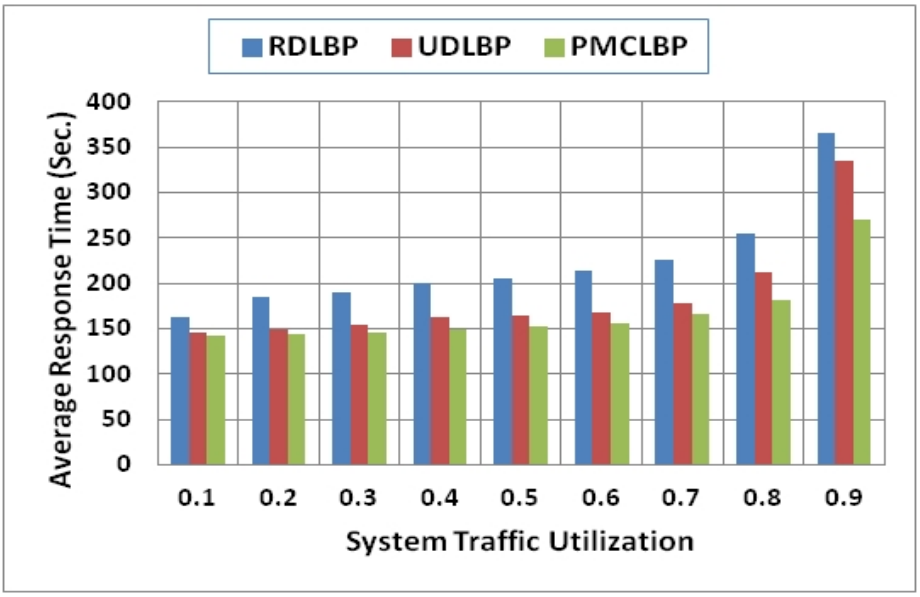

Fig. 3. Task average response time

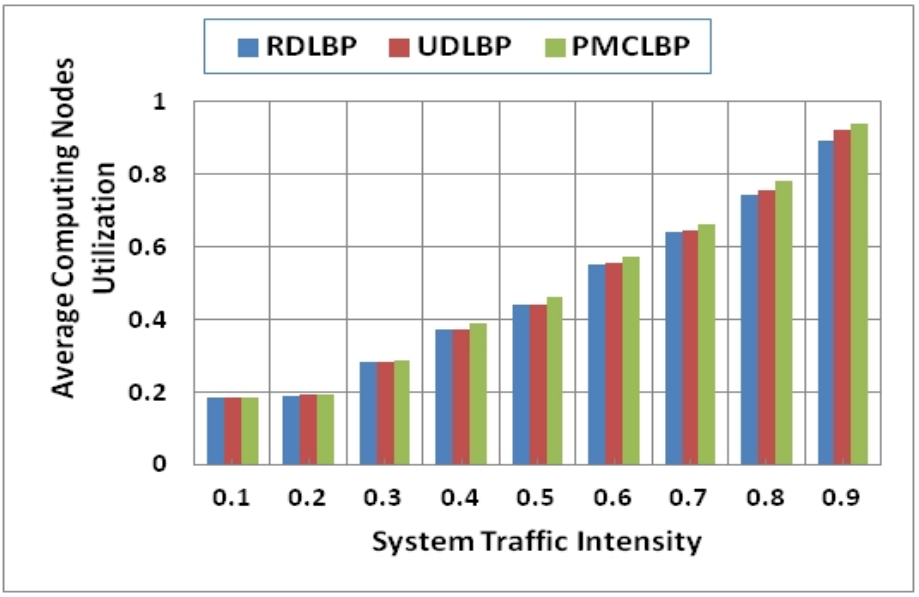

Fig. 4. Average computing nodes utilization

In the second experiment, the effect of varying number of computing nodes n form 2 to 128 on the system performance using the same performance metrics is studied. **Fig. 5** shows the effect of changing number of computing nodes on the average task response time using the three evaluated scheduling strategies. It is clear from that figure that PMCLBS outperforms the RDLBS and the UDLBS. The improvement is of a certain magnitude for moderate number of computing nodes. The performance of the three studied load balancing strategies converges when the number of computing nodes is low or high. This is logical because when the number of computing nodes is low, the computing nodes become highly loaded and almost all tasks suffer from waiting in the queues. Also, when the number of computing nodes increases, their utilization decreases because many of them will be available. This removes the effect of balancing the workload using the three evaluated load balancing strategies, and this explains why the response time obtained by the three strategies is almost the same for low and high number of computing nodes. This result is ensured in **Fig. 6** which presents the effect of varying the number of computing nodes on their average utilization using the three evaluated scheduling strategies. It is noticed from that figure that the computing nodes utilization decreases as their number increases. Again, one can notice that the PMCLBS outperforms the other two strategies in terms of average computing node utilization when the number of computing nodes is moderate. Also, when the number of computing nodes is low or high, the performance of three studied scheduling strategies is almost the same for the same reason explained earlier.

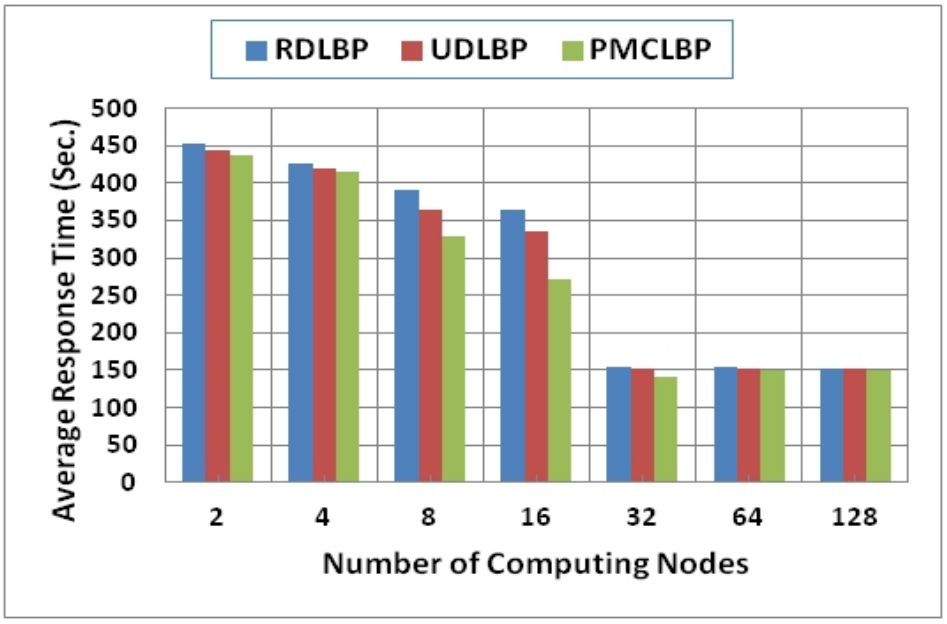

Fig. 5. Average response time versus number of computing nodes

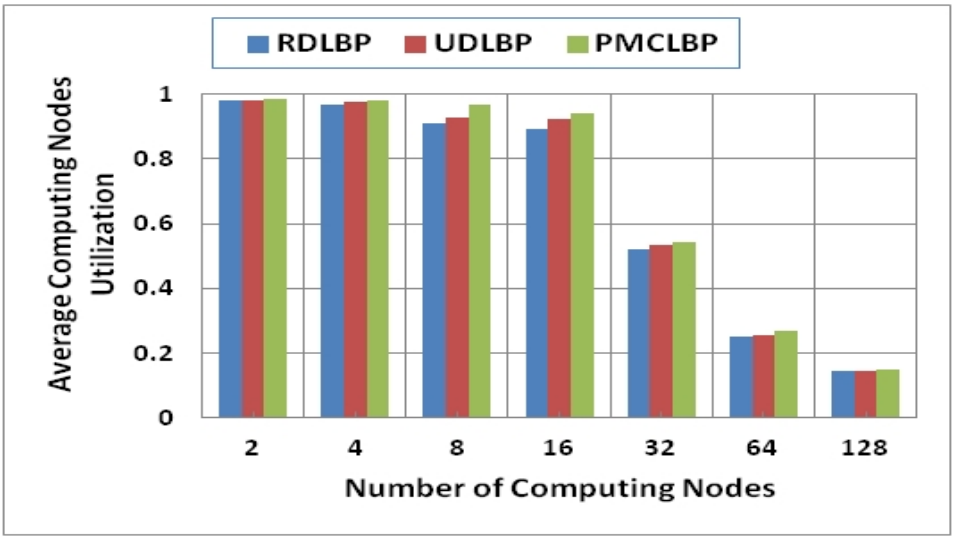

Fig. 6. Computing nodes utilization versus number of computing

5. Conclusion

In this research paper, we studied the problem of scheduling different classes of user jobs on heterogeneous distributed computing systems. A multi-class load balancing strategy aiming to minimize the average per-class response time is proposed. The performance of the proposed multi-class load balancing strategy is compared with that of the random distribution, and uniform distribution load balancing strategies. The simulation results show that, the propose scheduling strategy outperforms the random and uniform distribution load balancing strategies in terms of average system response time, and average computing nodes utilizations. This improvement is clear for moderate system workload. When the system workload is heavy or light the performance of the three studied scheduling strategies converges. In the future, an extension to the proposed multi-class load balancing strategy to be able to deal with more complicated hierarchical models that reflect the real models will be studied

6. Acknowledgments

The authors would like to extend their sincere appreciation to the Deanship of Scientific Research at King Saud University for its funding of this research through Research Group Project RGP-VPP-229.

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