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AN EFFICIENT JOB SCHEDULING TECHNIQUES WITH OPTIMAL RESOURCE ALLOCATION FOR MULTI PRIVATE CLOUD ENVIRONMENT

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Abstract: Cloud computing technology has a large number of computing resources running in the data center in order to make the best use of cloud resources and maximize the benefits of cloud providers. Virtual Resource Professional uses task planning methods with virtual machines and automated task planning to improve service quality and resource performance. Real-time challenges and regular customer demands make business planning a difficult problem for NPs. Cloud computing resource allocation strategy should be intelligent and should cover key resource criteria. This issue focuses on optimal resource allocation algorithms in multiple private cloud environments. A proposed approach for scheduling multiple jobs in a scalable and heterogeneous Hadoop system in the cloud based on the number of incoming jobs and available resources. A new scheduling scheme is proposed for large cloud environments to solve problems that mainly depend on efficient resource allocation and job scheduling. The proposed scheduler outperforms the above state-of-the-art scheduler models with relatively better runtime efficiency. Finally, it handles efficient dynamic resource allocation and job scheduling strategies to achieve better cluster performance in terms of execution time and efficiency.

Keywords: *Job Scheduling, Private Cloud, Resource Allocation, Optimized Scheduling Algorithm*

1. INTRODUCTION

Cloud computing has become one of the most exciting areas of expertise in the modern era. Users can access cloud resources on demand from anywhere in the world. Cloud service providers (CSPs) own a large number of data centres, incentivized by the profits users pay to access services, and users are attracted by the opportunity to reduce the cost of fully deploying these services [1].

Cloud computing uses payment as policy. It provides a policy pay based only on the user's resource usage. It provides flexibility to the cloud user to increase or decrease their service requirement based on their usage and service charge [2]. Small businesses that cannot afford their IT infrastructure due to lack of technology, cost and security are the biggest users of the cloud. The cloud offers all computing services in a pay-as-you-go model. So, it is very easy to have a cloud and need a computer service at any time. Businesses can change the demand for services, so the cloud also provides flexibility to enable cost-effective delivery of services.

Table 1.1 Cloud Service Model and their providers

Cloud Service Models	Few Cloud Providers
SaaS	Salesforce.com, Gmail, Google Docs, Base Camp, Fresh books
PaaS	Force.com, App Engine, Azure
IaaS	Go Grid, Rack space, AWS

Services are provided in terms of Infrastructure (IaaS), Platform (PaaS) and Software as a Service (SaaS). Various users are using different services as per their requirement which is shown in Table 1.1 and thinking about how it will be delivered for computing.

1.1 Private Cloud:

This model provided cloud services dedicated to a particular organization. Cloud services can be provided by same business domain or third party. The services can be available within or out of premises. Some public CSP that offer this competence include Skytap Virtual Lab, OpSource Cloud, and Amazon Virtual Private Cloud[3].

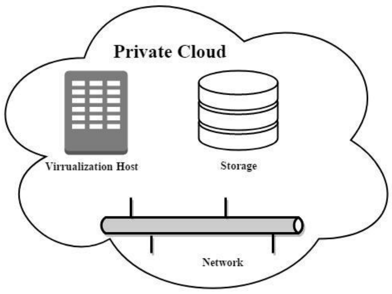

Fig 1.1 Private Cloud

Cloud computing is still in its progressive stages; however, it has exhibited new areas to clients and engineers who can profit by economies of scales, commoditization of benefits and conformance to programming principles. Its qualities i.e., scalability, flexibility, low boundary to passage and a utility sort of delivery make this new paradigm rapidly striking [4-6].

2. LITERATURE REVIEW

Cloud computing depends on using distributed resources which are simply allocated, or deallocated. Cloud computing has emerged as a new technology. It is rapidly expanding as a result of the huge development of internet services. This technology is characterized by providing services to consumers and sharing the cloud resources between the customers.

2.1 Multi Cloud Environments

Cloud computing is believed to be born in 2006, when the Amazon Web Services (AWS) launched its Simple Storage Service (S3)[5]. With cloud computing came terms such as cloud computing private, public, and hybrid and some acronyms such as SaaS, PaaS, and IaaS. The key players in the cloud computing system are service providers, users (consumers), and the internet which is the link between service providers and users. This is illustrated in Fig. 2.1.

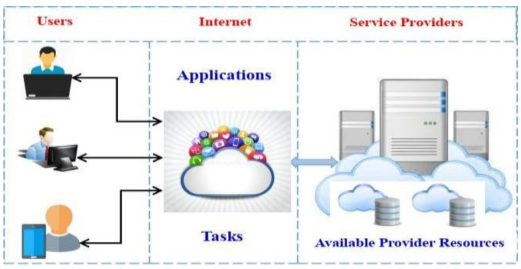

Fig. 2.1 Key players of Cloud computing

2.2 Multi-Cloud Computing Service Measurement

The services given by the cloud specialist organization in distributed computing climate are fluctuated and customized to meet client necessities. The services come as applications and types like stages and framework. Service level understanding is marked and submitted to the chief of service level arrangement after an exchange as per the prerequisites of nature of service depicted by clients, different responsibility highlights, different arrangements of necessities, and supplier portrayal of the accessible assets [6-8].

2.2.1. Resource utilization

Job scheduling in cloud computing environment is an important challenge because it concentrates on enhancing the resource utilization, namely computation power, memory, bandwidth, storage, etc. To achieve effective job scheduling, minimum make span and response time should be utilized by executing the jobs within a specific time [9].

Genetic algorithm (GA) is one of the meta-heuristic algorithms that attempts to obtain the optimal solutions for these difficult problems. The concept of a genetic algorithm is the biological development of chromosomes and survival of fittest, which gets the best solutions using remerging with the others.

2.2.2. Dynamic Resource allocator (DRA)

The load balancing functionality can be achieved by finding skew values for all running VMs and then predicting future load. In this strategy, the migration of VM can be done for realizing overload condition of the system and also for load prediction[10].

2.2.3. Dynamic Resource Allocation Strategy

A DRA strategy based on features of tasks that focus on allocating VMs based on priority of job. The priority of the job is set by calculating the estimated completion time. The lease of resources is requested so that the suspension and resumed of the job can be done accordingly [11].

2.2.4 Works on Optimization Approaches

A few of the bio-inspired algorithms are on the basis of swarm-intelligence. For instance, Ant Colony Optimization, Particle Swarm Optimization, Firefly Algorithm, Cuckoo Search and

Bat Algorithm. Amongst these innovative algorithms, numerous algorithms have gained popularity because of their high proficiency, for example, Particle Swarm Optimization, Firefly algorithm and Cuckoo Search, etc. Various nature-inspired optimization algorithms are discussed in the following sections [12-19].

Table 2.1 Comparative analysis of various Optimization Algorithms

Heuristic Algorithms	**Parameter Involved**	**Working Mechanism**	**Features**	**Application Areas**
Genetic algorithm	Population size, mutation and crossover probability	Survival of the fittest in natural evolution	Easily transferred to existing simulation and models	Good in searching large and complex search space.
Particle Swarm Optimization	Learning factors, number, dimension and range of particle, max change of particle velocity	Optimal solution obtained by the movement of the particle in the problem space	Simple calculations, no overlapping and mutation calculations	Scheduling problems, data mining, combinatorial optimization
Ant Colony Optimization	No of ants, initial pheromone value, weight and evaporation rate	Ants use “pheromone deposition” concept for finding the optimal route.	Used in dynamic applications	Scheduling problems, network transportation and routing systems
Artificial Bee Colony	Employed bees, onlooker bees and scout bees	Collected information is shared by performing a waggle dance	Intelligent behaviour of honey bees for solving optimization problems	Solving clustering, travelling sales man problem
Cuckoo Search Optimization	No of nest, levy flight solutions	Use the new and possibly better solutions (Cuckoos) to replace a worst solution in the nests	Simple implementation less no of parameter in comparison to PSO, GA and ACO	Job scheduling. To locate the best, possible server in distributed systems clustering

3. SA-BSO Optimization for Job Scheduling in Multi objective Task Scheduling

A new task scheduling system based on artificial optimization methods. The implementation of the proposed method provides a multi-objective optimization that uses the adaptive brainstorming optimization (SA-BSO) method to plan a business warehouse in a multi-cloud environment. The main emphasis of the mission planning approach is on resource optimization, but the proposed SA-BSO defines three quality criteria such as cost, time and resource utilization. The newly developed algorithm improves the overall performance of virtual machines by making full use of cloud resources while reducing operational costs and overall task execution time. The task scheduling problem is a major concern in performing tasks in a hybrid computing system. The main issues are runtime, optimal CPU resources and operating costs.

3.1 Initial Dataset

In the initial dataset, TC and TM represent the total CPU and total memory respectively. The mapping of TM with VMs shown by assigning the one-to-one mapping between CPU and corresponding memory and calculating the sum of the complete task, as shown in Error! Or Reference source not found. For example, the CPU cost for $VM1$,2, $VM3$, $VM4$ are taken as 1.5, 1.6, 1.7, 1.8 respectively. Similarly, the memory cost for $VM1$,2, $VM3$, $VM4$is 3.0, 3.5, 7.5, and 4.2 respectively.

Table 3.1 VMs allocation with CPU and memory

Virtual Machine	**CPU**		**Memory**	
CPUs	**CPUs**	**CPU Cost**	**Memory Units**	**Memory Cost**
$VM1$,	3	1.5	3	3.0
$VM1$,	2	1.6	4	3.5
$VM1$,	3	1.7	3	7.5
$VM1$,	4	1.8	5	4.2
CPU/Memory	TC=12		TM=15	

Table 3.2 shows the initial datasets of four different applications and the representation of these applications $b1$, $b2$, $b3$, $b4$, initial tasks are $rJ1$, $rJ2$, $rJ3$…..., $rJ10$, application deadline $d1$,$d2$,$d3$,$d4$ is assigned as 22, 23, 25, and 22 respectively. The runtime $t1$,2, $t3$, $t4$ for four applications are corresponding 3, 3, 2, and 4.

Table 3.2 Initial Dataset Representation

publication Group	Initial Task	Deadline in hrs	Runtime in hrs
$b1$	$rJ1$, $rJ2$, $rJ3$	d1=22	t1=3
$b2$	$rJ4$, $rJ5$	d2=23	t2=3
$b3$	$rJ6$, $rJ7$, $rJ8$	d3=25	t3=2
$b4$	$rJ9$, $rJ10$	d4=22	t4=4

Algorithm: SA-BSO Optimization for Job Scheduling in **Multi objective Task Scheduling**

Cloud

Randomly generate individual initiatives Lj and evaluate them

while (!MAX)

// Operator Grouping

Convert the Lj to m clusters

Best individual = CC // CC□cluster centre

// Replacing operator

If (random(0,1) < Pr)substitute

Select an arbitrary cluster and with new random value, substitute the CC

End-if

for (L1 to Lj) do

if (random(0,1) < Pr)

Select a random cluster

if (random(0,1) < Pr-centre)

To generate new initiative, add arbitrary values to the selected CC

Else

Perform addition of Arbitrary values with random initiative and produce a new initiative value

End-if

Else

sort the list of VM received in descending order

n←0

for m←0 to Ti do

If n≥0 then

bind Tm to VMm, m++

if j== no of VM then

J=0

end if

End-for

End-while

Performance evaluation of the proposed brain-inspired biological optimization (SA-BSO) method for the cloud computing workshop problem. The proposed system uses the SA-BSO algorithm for timing problems that take into account various QoS parameters in a cloud environment.

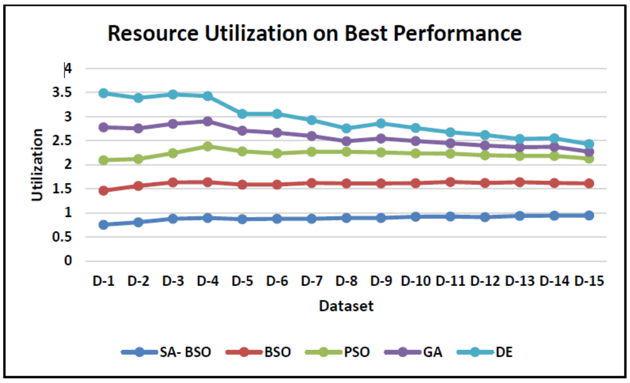

Fig 3. 1. Resource Utilization on Best Performance

The proposed SA-BSO method at D-2 has the best performance on cost parameters. The proposed approach improves over the PSO, GA, and DE techniques by 39%The worst performance was better at 8.2%, 45%, 50.82%, and 50.The models BSO, PSO, GA, and DE had 27%The performance for the presented SA-BSO is 72.1%, 74.6%, 88.5%, and 89.65%, with a standard deviation of 55.85%The algorithm outperforms the BSO, PSO, GA, and DE algorithms by 66% when compared.

The proposed algorithm is implemented in the simulated environment of cloudsim. The proposed algorithm works in real time dynamic environment so it is tested on different VM (with different speed) and tasks of different size. There are many different VM with different sizes and different tasks with different sizes for a real-time environment. The size of the tasks ranges from 1000 to 8000 and the Quality of Service (QoS) ranges from 0 to 9. The low quality of service shows a high priority and the VM processing range is 1000-5000 MIPS.

Table 3.3 Workload of VMs and Tasks

Workload	Number of VMs	No. of Tasks
1	4	25
2	4	60
3	4	120
4	4	250
5	6	60
6	12	120

Table 3.4 Execution Time of proposed Algorithm on different size tasks

T-ID	Execution Time			
	No. of Tasks	**MoTS**	**RR**	**FCFS**
1	10	1.1	1.5	1.6
2	20	1.3	1.8	2.1
3	30	1.6	2.3	2.9
4	40	1.8	2.9	3.6
5	50	2.1	3.5	3.9

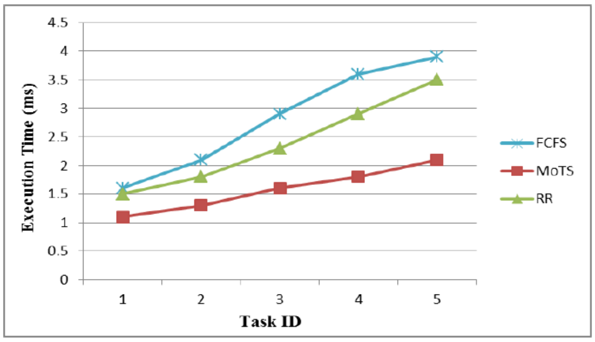

Fig 3.2 Execution Time of proposed algorithm with FCFS and RR

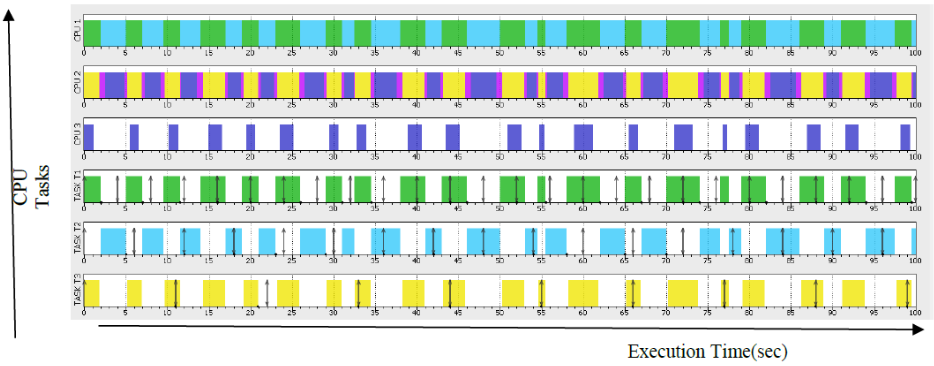

Fig 3.3 Traditional Evolutionary Algorithm (PSO)

The specified business values are traditionally used first. Prioritization is always an important factor in traditional business planning methods. Basic tasks are organized by the task scheduler and assigned to the appropriate VM. The algorithm is then implemented using the cloudsim simulator, which is compared to other traditional algorithms. Current research focuses on mapping between VMs and tasks by reducing costs and productivity, using human-inspired applications for multi-cloud environments, and providing a comprehensive system to the cloud provider and end user. From the experimental analysis, it was found that the algorithm was able to produce better solutions than those found by current state-of-the-art approaches by between 10% and 15%

4. CONCLUSION

The optimization of resource allocation strategy in cloud environment is a mail purpose of the research. The purpose of the research is to improve the allocation of resources in the cloud. In this work, both type of algorithms are used to improve the allocation of resources. The priorities of the submitted task are initially used in the traditional way. The purpose of the research is to improve the allocation of resources in the cloud. In this work, both type of algorithms are used to improve the allocation of resources. The priorities of the submitted task are initially used in the traditional way. Priority is always a major factor in traditional job scheduling methods. In the first part of the research, multi-objective priority calculation is used to calculate the priority of the task, taking into consideration different parameters. The priority tasks are scheduled by the job scheduler and allocated to the corresponding VM. The algorithm is then implemented using the cloudsim simulator, where it is compared with other traditional algorithms. The present research work emphasizes the mapping between VMs and tasks with minimizing the cost and makespan, by implementing human-inspired schemes for multiple cloud environments, and delivering a substantial framework to the cloud provider and end-user.

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