Meta-heuristic Algorithms for Resource Allocation in Cloud

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Abstract. Resource allocation in cloud computing is inherently a challenging task due to the increase in the number of cloud users working on multifarious cloud applications in some of the infrastructure. The majority of resource allocation techniques existing till have focus on providing performance driven by the workload of the applications from diverse domains like scientific and business. This paper presents a detailed review of meta-heuristics algorithms for resource allocation in cloud computing environment. The reviewed meta-heuristic algorithms are capable of achieving much higher performance, reduction in a cost, reduction in time, improve utilization of resources, improve energy efficiency while resource allocation in cloud.

1. Introduction
Cloud computing is a paradigm that allows ubiquitous, demanding approach to a shared pool of optimized computing resources such as servers, applications, storage, networks and services that can be quickly and easily delivered which is displayed in “Figure 1. Resource allocation in cloud” [1]. The resource pool needs to be supervised expertly to reduce energy costs and provide end-user support services in the form of negotiated quality of service (QoS), developed in the form of Service Level Agreements (SLA). Generally services offered in three basic models: Infrastructure as a Service, Software as a Service and Platform as a Service [2]. The resources are also highly heterogeneous and virtualized to allow the execution of multiple applications on a single physical machine. The user applications are contained in a virtual machine and are instantiated on a suitable physical machine when it is required. The applications have contentious resource requirements in terms of resources like a CPU, memory, processing speed, network bandwidth and response time. Resources are provided and shared accordingly consumer demand. To manage the resource requirements of number of users, cloud market such as, Flexiant, Microsoft, Amazon, Google, Gogidi, etc., created high number of data centers[3].These data centers have a variety of sources and each resource is tied to its own power consumption. Apart from many benefits; Cloud data centers also suffer from a problem like large amount of power consumption [4].

In addition, allocation of resource approach is used to assure that all applications requirements are satisfactorily met. For all these purpose, allocation of resource in cloud computing environment is one of the major challenges. Aside from, allocation of resources for performance, there are other challenges like, allocating enough resources to user applications to fulfil QoS, industry and researchers to reduce energy consumption with carbon footprints [5]. Energy consumption of resources and its utilization are highly coupled [6]. So, for proper use of cloud resource administration, it is important to refine the efficiency and process of scheduling matching tasks and resources with the size of a task and initiating a four-dimensional resource structure at the business level, the operational level, the cell level and the service level[7].In this paper, the emergence of cloud computing with different resource allocation strategies has been discussed by using various parameters such as utilization, customer
satisfaction, price, reliability, demand, efficiency, power generation, resource utilization and the last but most important aspect of cloud quality (QoS)[8].

![Resource allocation in cloud](image)

**Figure 1.** Resource allocation in cloud.

### 1.1. Metaheuristics Approaches

Standard resource allocation methods are not enough for cloud as they are depended on virtualization mechanism with distributed environments. Due to heterogeneity in the strength of Hardware, load balancing, and features towards meet the Service Level purpose of cloud purchaser applications, Cloud computing propose new challenges for manageable and flexible resource allocation. The utmost objective of computing cloud computing resources is to maximize profits received by cloud suppliers and reduce the financial costs of cloud users [9]. However, traditional approaches are much easier to understand, and easier to use than other algorithms such as analytical processes and identical numerical programming. The outcome is not guaranteed to be correctly generated by approaches [10].

Cloud computer programming associated to a group of issues called as NP-hard drives due to the number of solutions, it take long time to reach the right one. None of the approaches can make the correct solution within a multinomial time to resolve these issues. In the cloud computing, it is better to discover a more efficient solution, but in the short term. Meta-heuristic based methods have proven to attain ideal solutions within sensitivity period of time for such issues [11].

“Meta” and “heuristic” come from Geek, means “higher” or “beyond” and later meaning “know” or “investigate.” Heuristic techniques have been used without assurance feasibility or accuracy for a suitable solution with low computational cost. To strengthen the effectiveness of heuristic processes using metaheuristics techniques, many methods are examined to enhance the efficiency of metaheuristics in algorithms. In addition, current algorithms have some functionality such as lower optima coverage, higher integration rate, more computational time, more complex operators and the formation of a real or binary search environment. Therefore, introducing new meta-heuristic approaches to address weaknesses is a major problematic problem [12]. Some of the meta-heuristics algorithms details are given in “Table1. Some meta-heuristic algorithms from (1975 to 2019)”.

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**Table1. Some meta-heuristic algorithms from (1975 to 2019)**
| Sr. No | Algorithm                        | Introduced By                  | Year |
|-------|----------------------------------|--------------------------------|------|
| 1     | Genetic Algorithm (GA)           | Holland[14]                    | 1975 |
| 2     | Scatter Search (SS)              | Glover[15]                     | 1977 |
| 3     | Tabu Search (TS)                 | Glover[18]                     | 1986 |
| 4     | Simulated Annealing (SA)         | Kirkpatrick et al.[17]         | 1983 |
| 5     | Ant Colony Optimization (ACO)     | Dorigo[19]                     | 1992 |
| 6     | Reactive Search Optimization (RSO) | Battiti and Brunato[21]       | 1994 |
| 7     | Particle Swarm Optimization (PSO)| Kennedy and Eberhart[22]       | 1995 |
| 8     | Artificial Bee Colony Algorithm (ABC) | Karaboga[25]                 | 2005 |
| 9     | Harmony Search (HS)              | Geem et al.[24]                | 2001 |
| 10    | Differential Evolution (DE)      | Storn and Price[23]            | 1997 |
| 11    | Shuffled frog leaping algorithm  | Eusuff, Lansey & Pasha[28]     | 2006 |
| 12    | Teaching Learning Based Optimization (TLBO) | Rao et al. [37]             | 2011 |
| 13    | River formation dynamics         | Rabanal, Rodríguez & Rubio[31] | 2007 |
| 14    | Artificial Bee Colony Algorithm (ICA) | Atashpaz-Gargari[29]     | 2007 |
| 15    | Firefly Algorithm (FA)           | Yang[32]                       | 2008 |
| 16    | Honey bee Mating Optimization (HbMO) | Haddad et al.[27]        | 2006 |
| 17    | Intelligent Water Drops (IWD)    | Shah-Hosseini[30]              | 2007 |
| 18    | Krill Herd (KH)                  | Gandomi and Alavi [38]         | 2012 |
| 19    | Spiral Optimization (SO)         | Tamura and Yasuda [36]         | 2011 |
| 20    | Cuckoo Search (CS)               | Yang and De [33]               | 2009 |
| 21    | Gravitational Search Algorithm (GSA) | Rashedi et al.[34]       | 2009 |
| 22    | Bat Algorithm (BA).              | Yang[35]                       | 2010 |
| 23    | Teaching Learning Based Optimization (TLBO) | Rao et al. [37]             | 2011 |
| 24    | Gravitational Search Algorithm (GSA) | Rashedi et al.[34]       | 2009 |
| 25    | Interior Search Algorithm (ISA)  | Gandom[40]                     | 2014 |
| 26    | Swallow Swarm Optimization (SSO) | Neshat et al.[39]             | 2013 |
| 27    | Gradient Evolution Algorithm (GEA) | Kuo and Zulvia[41]        | 2015 |
| 28    | Water Wave Optimization (WWO)    | Zheng[42]                      | 2015 |
| 29    | Killer Whale Algorithm           | Biyanto[43]                    | 2016 |
| 30    | Rain Water Algorithm             | Biyanto[44]                    | 2017 |
Many aspects of meta-heuristics exist, and the diversity of novel approaches is often promoted by the distribution of resources in various fields. There are numerous outstanding and significant meta-heuristic algorithms in the section of cloud computing environment for the management of resources such as Simulated Annealing (SA), Ant Colony Optimization (ACO), Genetic Algorithm (GA), Cuckoo Search (CS), Glowworm Swarm Optimization (GSO), Artificial Bee Colony Algorithm (ABC), Firefly Algorithm (FA), Honey bee Mating Optimization (HBMO), Swallow Swarm Optimization (SSO), and many more. Some of the most important metaheuristic approaches are listed in Table 1[13].

For allocation of resource in Cloud Computing, some of the Meta-heuristic approaches are used like Teaching Learning Based Optimization (TLBO), Artificial Bee Colony (ABC), Harmony Search (HS), Ant Colony Optimization (ACO), Gravitational Search Algorithm (GSA), Cuckoo Search (CS) Algorithm, Firefly Algorithm (FA), Genetic Algorithm (GA), Shuffled Frog Leaping Algorithm (SFLA), Particle Swarm Optimization (PSO) are discussed in next section.

An agenda of this paper is to study and analyze the Allocation of resources into cloud environment with various metaheuristics techniques. The flow of the paper is; Section 2 contains the Review and Analysis of metaheuristic algorithms used to solve the allocation problem of resources. In Section 3, we present the conclusions and future scope.

2. Analysis of the Algorithms

In Cloud Computing, it is preferable to explore for the right resource allocation solution in the limited time. Methods depend on Meta-heuristic have been proven to produce the right results at the right time for this type of issues. An overview of cloud computing depends on seven advanced metaheuristic techniques, and a survey of these metaheuristic processes is presented.

2.1. Teaching Learning Based Optimization (TLBO)

TLBO approach, a metaheuristic optimization method motivated by the classroom environment. It was prejudiced which can simplify the process of troubleshooting optimization [47].

TLBO has been used as a meta-heuristic approach to develop a service request scheduling for cloud computing components, where the programming between number of users and virtual machines has been done. With the help of the TLBO technique, the calculation of the optimal solution for selecting the appropriate user combination with a pair of virtual machines that resulted in a reduction in delay, maximizing performance and thus helping to use optimization rather than full implementation of the complex and time-intensive algorithm to optimize cloud environment has been done [48].

TLBO and grey wolves optimization algorithm (GW) hybrid algorithm, accurately balances priorities and considers performance based on time, cost, and avoidance of local optimum traps, resulting in less waiting time [49].

2.2. Gravitational Search Algorithm (GSA)

GSA was built on the principle of gravity along with the concept of mass interaction. The GSA approach uses the concept of Newtonian physics and its researchers were a collection of many masses. At GSA, there was a unique system for masses. Using gravity, each mass in the network can see other masses condition. Hence, gravity is a way of conveying information between distinct entities [34].

For solving nonlinear problems GSA has a high proficiency. GSA has been used for allocation of resource in cloud computing environment. The proposed method shows that, compared with the GA and GSA without fuzzy improvements, it receives nearly identical application reaction for resource allocation also provided resources for jobs with least mean flow and span of time with load balancing other approaches. Though proposed the path often evolves into a complete response to the several iterations than GA and does GSA approaches not trapped in the local optimum [50].
2.3. Ant Colony Optimization (ACO)
ACO draws insight from the destructive behavior of certain types of ants. These ants put the pheromone in the ground to mark a specific path, so that other members of the colony can follow the same path. Ant colony efficiency exploits the same way of solving optimization problems [51]. In this paper, we learned about proper allocation of resources of cloud, for the purpose of optimizing cost, quality of services, time and load balance of resources. The modified ACO algorithm has been used as a solution. However, more preparation is being done in this work, such as characteristics of resources and match between the job requirements, as well as the main ones selected sources of suitable candidate resources [52].

First, the new ACO algorithm first recognizes the power of existing resource nodes, examining specific features, for example, network attributes and response times to achieve a set of relevant calculations. Finally, jobs are scattered across relevant nodes [53]. The approach is predicted by the capacity of the obtainable resource node, at the time of allocation and analyzes of bandwidth use, network quality and response time [54].

2.4. Particle Swarm Optimization (PSO)
PSO approach, an appropriate meta-heuristic algorithm to optimize continuous nonlinear functions. This algorithm was influenced by the idea of bird cruelty, frequently seen in groups of animals, like flocks and in the sea in the concept to find the greatest solution[55].PSO contains a community called as swarm and each candidate(birds, fishes, insects) are taken as particles, they are developed by random situations and velocities.

This study has defined resource scheduling technique with Improve PSO (IPSO) algorithm for quality of service constrained resources, assumed as cross the evolution of the genetic approach and the Pareto method of Optimization. The outcome of the study proposes that the model can increase efficiency, and improve performance search speed, indicates a certain height [56].

To optimize the consumption of energy in the cloud data center, a more systematic allocation of virtual machine approach is proposed by the PSO process and a more efficient energy allocation of resource model. In this approach, the PSO stiffness function is as different as the rest of the finishing point between the energy consumption and the utility of resources. This approach can escape down to local optima, common to traditional approaches [57].

2.5. Harmony Search Algorithm (HS)
HS is a metaheuristic approach tries to mimic the process of singers' development in finding the perfect harmony. Recently, due to certain benefits, HS has received much attention. HS is easy to use, quickly converts to the right solution and gets a good enough solution for the right amount of time. The advantage of the HS algorithm has resulted in its application to problems of the use of different engineering environments [58].

A structured resource planning approach is needed for well use of cloud resources. Depends on HS, a new meta-heuristic technique is studied in this approach, to analyses the validity of the solution by using makespan. To evaluate the Harmony Search algorithm’s execution, CloudSim 3.0.3 tool has been used as cloud simulator .This study has represented that by using Harmony Search based cloud scheduling algorithm, the varying makespan (in seconds) has been expanding in number of cloudlets [59].

2.6. Firefly Algorithm (FA)
The FA is classified as swarm intelligence, meta-heuristic and nature-inspired, with an emphasis on the behavior of fireflies . In fact, a number of fireflies show bright light activities to serve as a means of attracting collaborators, communication, and warning of danger to hunters. In the design of the firefly algorithm, the objective function is associated with the flashing light features of the firefly community. Considering the optical principle of the light intensity, it is approximately equal in the square of the area, so that this objective can define the correct distance function between any two fireflies. In order to make the work more efficient, individuals are forced to move systematically or randomly in the population [60].
This study presented a new way of job scheduling using the FA to shorten the time to perform tasks. Proposed method depends on knowledge of resources and jobs like the length of job speed of resource and identifiers. Arrangement working on the proposed job scheduling approach initially produces a set of resources and jobs to create population by providing jobs to resources on the random basis and it calculates the number of people using a fitness value that indicates the time to perform jobs. Secondly the work used iterations to reconstruct population based on firefly behavior producing an excellent work schedule that provides less time for activities [61].

2.7. Genetic Algorithm(GA)
GA was proposed in 1970 by John H. Holland. GA is an algorithm for optimizing algorithms that mimic evolutionary processes. The process of biological evolution on chromosomes converts to the GA concept. It is depended on the concept of survivorship that is best suited to finding the best new solutions through reunification.GA are unwanted search processes designed to work on them large spaces involving wireless circuitry. These metrics are very similar, using locally distributed samples (number of threads) to generate a new set of samples.[62]

Allocation of resources has been done proceeding into account computational and the network requirements for jobs and optimizes task time as well as power center data usage. For allocating the large number of tasks to servers on the data centers within the given time, open source genetic frameworks known as JMetal express found utilizing in the test results[63]. Assigning suitable resources to Virtual Machines (VMs) is a main issue for manager who manages the resources. The opportunity for a genetic Algorithm (GA) to solve the service allocation problem also proposes a new technique for optimizing the outcome of the decision making procedures [64].

2.8. Artificial Bee Colony Algorithm (ABC)
It is an approach introduced in 2005, which is used to solve the continuous optimization issues. In this algorithm, only 1D food position is updated by employed and unemployed bees. During the search process the artificial agents use, one solution update rule. It consists of two kinds of bees: one is employed and second is unemployed. The employed bees gather the fluid from food resources and share the locations of food with other unemployed bees whereas, other bees search for the food sources by using the data delivered by employed bees. It is a energy resource usage process model that has been studied to optimize cloud resources and improve their use. The ABC depends on the process of powering the resources that are the same size as the model taking into account the allocation of functions to cloud computing resources. In addition, it supports decreasing the power consumption of clouds through server interfaces through the fact that visualization reduces user-desired tactics[65].ABC based energy aware resource usage method correspondent to the design that is designed to distribute functions and resources to the cloud. Efficiency of the given approach is tested with existing techniques by using CloudSim tool. The test results indicate that the proposed process is more than existing strategies by reducing the energy and operational time of cloud-based applications [65].

2.9. Cuckoo Search(CS)
An approach was designed by Yang and Deb in 2009, and it is a biological encouraged computational search approach, this optimization technique is based on upbringing actions of Cuckoo. This algorithm works on the upbringing performance of Cuckoo in addition with Levy Flight actions of fruits flies and birds. This study presented a Hybridized Optimization approach which is a hybrid of 'Shuffled Frog Leaping Algorithm' (SFLA) and 'Cuckoo Search' (CS) approaches. This method overcomes existing performance constraints such as the HABCCS approach, the GTS approach function; the krill herd approach, and combines the benefits of SFLA and CS. Like this, the SFLA phase is performing the previous steps; it starts the application size, generates requests, and estimates the SFLA hardness value, sorting, classifying and evaluating user requests. CS approach has the advantage of easy testing and is used in difficult circumstances. In this stated system, the speed of the application, the sizes are evaluated. These tests are used to allocate services on the server side. Non-commissioned times are
utilized in this method. Test results show that this method works well comparisons with other related methods [66].

Further comparative analysis has been done of existing meta-heuristic algorithms for allocation of resources in Cloud Computing in “Table 2. Comparison of metaheuristic approaches for allocation of resources in the Cloud”.

| Authors           | Meta-heuristic | Environment | Problems                         | Achievement                                      | Year | Simulation Tools |
|-------------------|----------------|-------------|----------------------------------|--------------------------------------------------|------|------------------|
| Shrivastava et al. [48] | TLBO          | Cloud       | Service Request Scheduling       | Performance enhancement and reduction of delay    | 2017 | Not mention      |
| Shooli et al. [50]   | GSA           | Cloud       | Allocate resources to tasks on VM| Less mean flow time and make span and more load balancing | 2020 | Not mention      |
| Wei et al. [52]     | ACO           | Cloud       | Optimal resource allocation      | Cost optimization, QoS, time and load balancing of the tools. | 2015 | Not mention      |
| Hu WX et al. [53]   | ACO           | Cloud       | Dynamically Resource Allocation  | Reduce Response Time and Enhance Performance      | 2013 | GridSim          |
| Liang Y et al. [54] | ACO           | Cloud       | Efficient Resource Allocation    | Enhance Performance.                             | 2013 | CloudSim         |
| Wang, Yan, et al. [56] | PSO          | Cloud       | Cloud computing resource allocation | Enhance the effectiveness, and better search speed. | 2019 | Not mention      |
| An-Ping X et al. [57] | PSO          | Cloud       | VM Allocation                    | Improve Energy efficiency                        | 2014 | CloudSim         |
| Malik et al. [59]   | HS            | Cloud       | cloud scheduling                 | Fitness of Solution.                             | 2016 | CloudSim         |
| Esa et al. [61]     | FA            | Cloud       | cloud job scheduling.            | Less time to perform jobs.                       | 2016 | CloudSim         |
| Portaluri et al. [63] | GA           | Cloud       | power efficient resource         | Minimizing make span and power consumption of    | 2014 | jMetal           |
After a thorough analysis of the meta-heuristic approaches presented to allocate resources in cloud. It can be seen that the prospects for meta-heuristic methods work better. Meta-heuristic approaches act both on behalf of the cloud operator and the cloud provider. From the perspective of the cloud user, cost, response time, the make span and execution time are important, which are used as important parameters for the provision of services to the cloud computing. Another important aspect of the cloud provider is that the workload, use and power consumption play an important role.

Many metaheuristic techniques have used to provide the solution to serious problems such as right allocation of resources, energy aware allocation of resources, VM allocation, reduction in energy consumptions, dynamic resource allocation, power efficient resource allocation, cloud job scheduling, efficient resource allocation. And these capabilities are used in unique simulation tools such as Cloudsim, jMetal, GridSim, Java, Matlab and provide the closest solution for allocation of resources in the cloud computing.

3. Conclusion
In this study, some meta-heuristic algorithm has been reviewed for allocation of resources in cloud. Many strategies to increase the effectiveness of meta-heuristics are examined in these reviews.

However, the reviewed meta-heuristic algorithms are proficient at achieving much higher performance, reduction in the cost, reduction in time, improve utilization of resources, improve energy efficiency while resource allocation on cloud. In future, other meta-heuristics algorithms which have not been reviewed in this paper can be used for resource allocation in Cloud.

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