The Efficient Resource Scheduling Strategy in Cloud: A Metaheuristic Approach

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Abstract. The cloud computing is evolving as a high-performance computing platform due to broad-scale, flexible computational architecture and heterogeneous collection of autonomous systems. Cloud technology uses concept of virtualization for managing resources, which develops resource scheduling as a key issue. The scheduling of cloud tasks is an NP-complete problem and therefore irreconcilable with particular solution. Also, with the huge collection of a database system, the management of resources and tasks becomes complex with specific to the completion time requirements and cost constraints. To resolve this problem, a number of meta-heuristic algorithms have been developed. Due to redundant wastage of resources and time, the under and over-provisioning is one kind of issues leads to either degradation in performance or wastage of cloud resources. To overcome these kinds of problems, we introduce a task scheduling approach by incorporating reinforcement learning along with the nature-inspired meta-heuristic optimization to maximizing cloud throughput, minimizing completion time & production cost in IaaS cloud. By reinforcement learning, the agent will choose appropriate action among a set of available actions and the scheduler succeeds towards task allocation resulted to decrease makespan and increasing system utilization rate.

1. Introduction
cloud computing as a prominent platform allows the distribution of computing services as a metered service through the internet. Cloud offers dynamism, variability and elasticity-based services to its users. The explosive demand for cloud services not only opens up research challenge in cloud environment, as well as manifest it as the fifth essential utility along with other fundamental utilities (i.e., electricity, water, telephony and natural gas) [1]. Cloud is the set of linked nodes consisting of more than one united computing resource. Cloud computing is a model providing easy access to popular cloud resources on demand from users, as the national standard and technology institute has reported. Also, it can be managed with minimal intervention from the service provider as shown in Figure 1. [2][3]. The new technology of cloud computing offers a variety of services. In IaaS, a user may instigate a new project via the leasing of computational resources for example Amazon Web Service. Platform-based service (PaaS) is a category in which platform customer applications can be built and run. Google App Engine is the best example for this. SaaS enables customers to avail application services on rent rather than buying them e.g., Salesforce, Cisco WebEx [4].
The diversified as well as complex requirements for cloud services have increased the workload across the cloud over the last decade. Inefficient scheduling methods confront the issues of over-used and under-used services i.e., imbalanced resources [5]. The main purpose of the schedule is the allocation of tasks among cloud resources in ways which eliminate the problem of imbalance by planning an algorithm. Optimizing the Parameters of main performance indicator is also inevitable. Hence there is a need of efficient task scheduling approach not only to boost the whole cloud system's output but also to fulfil needs of its end-users [6].

The paper is structured as follows: Section 2 provides a brief analysis of related works. Section 3 explains some background information to understand the concept of scheduling over cloud followed by defining the task scheduling problem in section 4. Section 5 discusses about general framework of Metaheuristic based methods. Section 6 proposes a hybrid scheduling optimization method. Finally, in Section 7, we conclude the paper and present recommendations for future work.

2. Related Work
For scheduling the task/resource, most of the researcher suggested optimization technique either heuristic or meta-heuristic. The studies related to this category are discussed here. A research by Li et al. introduced an approach for minimizing the makespan which uses the load balance-based Ant Colony Optimization in Cloud [7]. Similarly, a study by Karaboga et al. suggested an Ant bee colony (ABC) method toward resolving the issues as well as discover the most suitable constraints in cloud environment [8]. A research by Mizan et al. resolved the job scheduling in Hybrid Cloud through modifying Bee Life method and Greedy approach to receiving an affirmative reply from the users has also been implemented [9]. From these points, it is concluded that most of them suggested optimization method for single objective.

The meta-heuristic method includes evolutionary computation, genetic algorithms, cuckoo search, iterated local search, ant colony optimization, tabu search, simulated annealing, particle swarm optimization, variable neighborhood search and others. Among those, CS (Cuckoo Search) and SA (Simulated annealing) are iterative algorithms. They generate solutions randomly which are further replaced by better ones, if any [10][11]. A study by Wang et al. proposed a workflow scheduling for multi-objective scenarios over the cloud platform. Especially, they have developed decentralized Deep-Q-network based multi-agent reinforcement learning model and applied stochastic markov model to attain correlated equilibrium solutions of workflow scheduling. The suggested model provided better
results when compared to the existing. However, the suggested model is insufficient to the historical QoS data [12].

A study by Ismayilov and Topcuoglu presented a dynamic multi-objective optimization problem (DMOP) to overcome the workflow scheduling issues and they adopted the leading non-prediction based dynamic algorithms. The obtained results have been validated with real time applications which shows better performance than traditional method. In future, they have planned to enhance the system performance by integrating machine learning technique [13]. From the review of the literature, we found that there is possibility of continuing and enhancing previously completed work in this field of task scheduling and load balancing process over the cloud environment. As overall, most of them suggested meta-heuristic method gives better result still, we are facing the issues in this research area.

3. Scheduling in Cloud Computing
Scheduling is responsible for selecting suitable virtual machines for performing tasks using heuristic or metaheuristic algorithms, as well as for determining if the other imposed constraints are efficiently achieved [14]. In the resource management, task scheduling is performed. Resource management is an umbrella practice with different stages, including the provisioning of resources, preparation of resources and monitoring of resources as shown in Figure 2.

![Figure 2. Taxonomy of Resource Management in Cloud [15]](image)

3.1. Resource Provisioning
Resource provision map with upcoming virtual machines to ensure a minimal usage cost and times for users as the service provider leverages the business without affecting the breach of SLA [15]. For cloud users, three key methods of resource provision are available, i.e. On-Demand Provisioning, Advanced Reservation and Spot Provisioning.

3.2. Resource Scheduling
Resource scheduling is done by allocating & mapping of resources. The aim is to allocate adequate resources to ensure that applications are able to use the resources effectively and on time [16]. Resource mapping is a process that maps workloads to available resources using user-specified QoS specifications to minimize costs, reduce runtime and improve profitability. Monitoring the performance of both physical and virtual infrastructures can be referred to as resource monitoring.

4. Cloud Task Scheduling Problem
Cloud computing is responsible for scheduling activities in the virtual machine layer. Task scheduling relies on appropriate mapping of task on VMs using a job scheduler while at the host-level a VM scheduler allocates the VMs into the physical hardware [17]. On the basis of a task dependence, tasks may be categorized as independent or dependent tasks. Scheduling based tasks is called Scheduling the workflow.
4.1. Problem Definition
Task scheduling focuses on finding an efficient mapping $C: T \times R \rightarrow \mathbb{R}^n$ in order to schedule $M$ number of tasks $T = \{T_1, T_2, \ldots, T_M\}$ among $N$ given resources over the cloud $R = \{R_1, R_2, \ldots, R_N\}$ in a way that fitness of $n$ given objectives $F = \{F_1, F_2, \ldots, F_n\}$ are greatly achieved. A list of notations used is given in Table 1 with their descriptions. Figure 3 illustrates this summary of the cloud task scheduling problem.

Figure 3. A Cloud Task Scheduling Problem [18]

| Symbol | Definitions |
|--------|-------------|
| $T_i$  | The $i^{th}$ cloudlet in the ready queue |
| $R_j$  | The $j^{th}$ number of cloud resource |
| $M$    | The number of cloudlets to be executed |
| $N$    | The number of available resources over the cloud that run the task. |

5. Metaheuristic-Based Techniques
Metaheuristics uses high-performance approaches for solving given problems and harmonies coordination between other search approaches like conventional & heuristics search techniques. The metaheuristic techniques often serve to obtain almost optimal solutions to the challenging scheduling issues over the cloud [19]. The key aims of the search Use metaheuristics can be summarized as follows:

- To find effective solutions to the given problems of optimization, which could be an NP-hard problem alone.
- Efficient identification of high-quality solutions with the highest possible objective characteristic values.
- Examine the solution space without being trapped in a particular area (especially local optima).

5.1. General metaheuristics Framework and Algorithm
A metaheuristics framework usually composed of these basic functions including transformation, computation and determination denoted by T, C and D respectively. The algorithm given below makes use of identifier $s$ and $v$ to denote the current solution and candidate solution respectively and $f$ represents the fitness value [20].

1) Transformation: In this phase current solution is evolved in order to get next state.
2) Computation: The objective function that is unique to the problem of optimization must be evaluated.
3) Determination: This phase leads the search process for their generations, intensity as well as diversity to achieve best possible results.

Metaheuristic Algorithm
1- Generate the initial solution space $s$
2- Unless the termination condition is fulfilled
3. \( v = \text{Transformation (s)} \)
4. \( f = \text{Computation (v)} \)
5. \( s = \text{Determination (v, f)} \)
6. End of loop

6. **Scheduling Optimizer: A Hybrid Method**

This research focuses on multi-objective task scheduling using bio nature-inspired meta-heuristic algorithms to optimize energy and processing time. Specifically, bio nature-inspired hybrid meta-heuristic algorithms (simulated annealing and cuckoo search method) to minimize the processing cost without the prioritizing tasks and management functions. Furthermore, will schedule and optimize the workflow completion time and cost by incorporating deep learning model. The architecture of proposed framework is illustrated in figure 4.

Both cuckoo search (CS) and Simulated annealing (SA) algorithms used extensively for solving optimization problems. CSA is a new population optimization algorithm that makes use of an insensitive tuning parameter in conjunction with the Levy flight. [22]. One major problem associated with most optimization algorithms, including the CS algorithm, is the early convergence of suboptimal solutions when applied to complex optimization problems.

Simulated annealing (SA) was a success for both discreet and ongoing problems as the single solution search algorithm. The SA algorithm improves the search process because it substitutes current solutions with bad ones, thus increasing chances of avoiding local optima [23]. Therefore, this research merges both CS and SA algorithm and will be used as optimization method as elaborated using flowchart given in figure 5.

**Figure 4. Proposed System Architecture [21]**

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There are three components in the recurrent neural network—input, hidden and output layers with forward relation among all three layers [24]. CW-RNN is distinguished by partitioning the neurons of the hidden layer into g modules each with its own clock rate and weight matrices of hidden layers get updated at different time steps as shown in figure 6.

**Figure 5.** Flowchart of Combined Optimization Method [23]

**Figure 6.** The CW-RNN Architecture with g Hidden Layers along Distinct Time Steps (Ti) from Faster to Slower Ones on the Right (Tg) [24]
By embedding deep learning model, the scheduler will update decisions based on provided criterion to obtain the goals that are difficult to optimize directly. The reinforcement learning, especially Clockwork-Recurrence Neural Network (CW-RNN) will be used for letting the agent to learn how to behave in an unknown environment and select the appropriate performance among a set of allowed actions on the basis of state and the feedback taken from environment.

7. Conclusion
This paper addresses resource scheduling with regard to multi-objective function in the IaaS Cloud context. Task scheduling is a difficult problem that greatly affects cloud performance. During the literature review we found that the previously conducted work in this area of scheduling & balancing in the cloud environment can be continued and improved. Each of the suggested methods has some demerits like maximum overloaded, delay, scheduling time and computation complexity. Additionally, few of the researchers only utilized a smaller number of tasks with single objective function. When related to the multi-objectives function, a single objective cannot offer maximum result. Hence this research presents a combination of metaheuristic-based optimization method and machine learning model which can manage broad search space applications efficiently. By deep learning process, the scheduler can provide better decisions as well as obtain the goals that are difficult to optimize directly. A further study of other computational parameters can be considered to effectively cope up with larger workloads also it can be extended to deal with more QoS metrics like security and reliability for more effectiveness.

8. References
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**Pseudo code of proposed hybrid model**

**Input:** Population PL, N- deep network generated solutions, Task T, set of processor PS, VM  
**Output:** optimal task schedule and load balancing  
**Begin**  
Do  
Test case set PS=T, PL, N;  
Initialize population with random population within predefined boundary  
// Optimization method  
Evaluate fitness of each task  
For i= 1 to T  
   For j=1 to VM  
      Completion time CT= Execution time ET + Ready time of task on VM  
   End for  
End for  
Do until all the unscheduled task are exhausted  
// deep learning model  
   For each unscheduled task  
      Obtain minimum completion time  
      Minimal energy consumption  
      Update scheduling decision  
   End for  
   until a termination condition is satisfied  
   return satisfy or reach maximum iteration  
obtain optimal result  
End do

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