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# Accurate Optimal Scheduling In Cloud Computing Based On Hybrid Bacterial Evolutionary And Bees Mating Optimization Algorithm

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For cloud computing, modern domestic and international information technology is a significant and frontier territory. The preparation of workflows plays a major role in cloud computing. The overall efficiency of the cloud system can be improved by planning workflows that are directly proportional to the accuracy of the planning methods.Optimization methods are most widely used to execute the task scheduling process. The optimization techniques used before performing the assignment scheduling method are particle swam optimization, genetic algorithm, and help vector machines. A new approach to conducting task planning processes based on the Hybrid Bacterial Evolution (HBE) framework is proposed in this paper.Various cost metrics such as execution cost, completion cost is considered to perform the fitness evaluation process. To evaluate the performance, various performance metrics such as Schedule Length Ratio (SLR), makes pan and speedup are evaluated. From the simulation result, it is very clear that the proposed techniques produced best performance in terms of all quality evaluation metrics.

## I. INTRODUCTION

Hundreds or thousands of computer jobs can be found in a wide variety of applications for science and industry. The workflow model is commonly used to define these applications with a direct acyclic graph (DAG), where a node corresponds to a task and the edge depends on the priority between tasks. Hundreds or thousands of computer jobs can be found in a wide variety of applications for science and industry.Using a forward acyclic graph (DAG), the workflow model is commonly used to describe these applications, where a node refers to a task, and an edge indicates the priority dependency between tasks. To optimize these key performance parameters, workflow planning focuses on how to delegate each task in the workflow to a particular time-limited computer resource. This issue has been widely researched in the distributed computing community for decades as an NP-hard problem, and has recently become a research subject in the cloud computing community [2].

Usually, cloud workflow scheduling algorithms aim to decrease with a fixed budget the total completion time or reduce the cost with a time limit. Due to the limited impact of data provided as new input, resources are often wasted in workflows for continuous processing. This is especially true when tracking, for instance, fire hazards, air pollution, and monitoring of near-Earth objects.In addition, Workflow Management Systems (WMS) typically neglect any performance economies used to evaluate the number of iterations needed for data processing[1]. Users can access a collection of resources to run applications at a very low cost of ownership by using virtual machines called examples in the IaaS cloud.Basically, planning for workflows on IAS clouds, also referred to as NP completion, is to find the right schemes for virtual machines to delegate tasks. Several metamorphic algorithms, such as the Genetic Algorithm (GA), the Particle Motion Optimization (PSO), and the Artificial Bee Colony (ABC) algorithm, have been proposed to solve the problem of scheduling workflows in the cloud world [5].

Due to the complex multicloud model of resource diversity of different cloud service providers, uniform in-band bandwidth, diversified interband bandwidth, and different cloud pricing models, better planning method is required to improve the quality of the service as well as the quality of the service. Reduces costs.Although several papers have addressed scheduling issues across distinct clouds, such as conventional distribution systems such as grids, very few papers have addressed this subject. The scheduling of workflows is the process of mapping each workflow task to related virtual machines and organizing tasks according to performance targets on each virtual machine.The sheer power of parallel computing in cloud computing has led researchers to discover its advantages and disadvantages when planning large data science workflows in the cloud environment [4].

Standard ABC has outstanding output and rapid rates of conversion, while conventional GAs have successful research capabilities. ABC can easily get caught up in the local optimum when applied to workflow planning problems, as global research productivity is low; GA has a slow integration rate in some instances due to a lack of strong local usage capacity.This paper proposes a hybrid solution based on the pay-as-you-go pricing model GA and ABC for the development of scientific workflows in IAS clouds in order to address the limitations of the two algorithms. The decoding heuristic is applied in a hybrid method in order to generate a valid plan. Compared with other algorithms, the effectiveness of one algorithm is measured to demonstrate its effectiveness in solving the problem of planning workflows in IaaS clouds [5].

This paper suggests a new way of performing workflow scheduling to improve overall system performance. A hybrid optimization approach is used to perform the job scheduling task. Various parameters are used to perform the connection optimization for the virtual machines. Fitness function is evaluated based on various cos metrics that is based on the computation time and work load. The main objective of the proposed work is given below:

1. To increase the overall performance of the cloud computing platform by assigning the user to a proper virtual machine using optimization process
2. To reduce the overload to the virtual machine to increase the load bearing capability
3. To avoid the interruption in connection while performing time consuming task.

The following is the remaining portion of this work. The brief information on various previous works performed to perform the workflow scheduling process is given in section II.In chapter III, proposed technique with hybrid optimization technique is described in a detailed manner.

Section IV describes the result analysis with various criteria used for work flow scheduling process. Section V concludes the paper.

## II. LITERATURE SURVEY

WeilingLi et al.Cloud computing has been suggested and how it is becoming a common tool for implementing science applications such as research workflows.This research focuses on workflow tasks that need to be performed with virtual machines that are consistent, general, or performance-limited, and focuses on reducing the execution time or execution costs of the workflow while meeting service quality requirements.This feature takes into account performance over time and lowers the cost of running a workflow deployed on IaaS clouds while retaining customer service level agreements. A case study based on real-world third-party IAS clouds and some established scientific workflows demonstrates that conventional approaches are beyond the reach of our proposed approach, especially those that only consider time or limited efficiency[6].

VahidArabnejad et al. implement a fresh heuristic forecasting algorithm that takes into account the timeline workflow of budget timeline planning (BDS), science budget planning, and cloud computing as a service (IAS). By offering a trade according to the scope of events between price and time, our challenge is to meet the existing budget and time constraints.Furthermore by conducting sensitivity analysis, we research the stability and efficiency of our algorithm. Overall, the findings show that BDAS considers more than 40,000 test cases that meet budget and time constraints in a realistic schedule. Our algorithm, in addition, is 23: 8% more efficient than modern algorithm[7].

Huangke Chen et al. introducing a modern scheduling system with three new features for security-sensitive workflows. Second, conduct a detailed theoretical study of how selective replication of previous tasks can be beneficial during data transfers and encryption times to avoid task start-up delays.Specify the last completion of the workflow tasks, demonstrate that tasks can be done before the final completion date of the job, and reduce costs without delaying task successors' start time and low-cost workflow lead time for the resource. We are developing a fresh approach to scheduling tasks using selective duplicates called SOLID on the basis of this research, which involves two key steps:1) Schedule tasks at regular intervals in the resource with selected duplicates of the previous tasks; and 2) Intermediate data encryption by efficient use of task downtime. Our findings show that the new SOLID approach takes precedence in terms of lead time, expense and resource utilization over existing algorithms[8].

Zi-Jia Wang et al.Swam Optimization (DGLDPSO) provides large-scale optimization, which refers to the preparation of particle cloud workflows for large-scale dynamic group training. Because of the following two advantages, DGLDPSO scale optimization is efficient. First the entire population is divided into a multitude of groups, which together grow into a distribution model of multi-group master-follower and form a distribution of PSO (DPSO) to increase the diversity of the algorithm.Second, DPSO adopted the Dynamic Group Learning (DGL) strategy to balance diversity and integration. As DGLDPSO is used to plan large-scale cloud workflows, an Adaptive Renewing Strategy (AROS) is modified to ensure that decisions are consistent with resource characteristics and that search behavior is meaningful and meaningless. Tests are conducted using a broad variety of test functions and large-scale cloud workflow scheduling examples to learn more about the efficacy of DGLDPSO. DGLDPSO and other existing big-scale optimization and workflow scheduling algorithms are seen or compared in the comparison results [9].

Peerasakwangsom et al. A scheduling solution approach that combines modern node clustering technologies and multi-object optimization and a highly non-dominant II-S genetic algorithm is suggested by the direct acyclic graph (DAG) model, also referred to as multi-level node clustering (MD3). ... The non-genetically valid sorting algorithm is the most recent extension of ENSGII (NSGA-3). As test benches, five well-known scientific workflows were selected: known cybershake performance tests, Epigenomics, LGO, montage, SIPT, and hypergomer. Three approaches are compared: e-NSGA-3 only, e-NSGA-3 peer grouping, and NNSGA-3 with MDNC. A discussion of the pros and cons of the proposed method is among them [10].

## PROPOSED WORKFLOW SCHEDULING USING HYBRID OPTIMIZATION TECHNIQUES

In the proposed method the work flow scheduling using the hybrid optimization technique is done using hybrid optimization technique. Workflow planning, as shown in Figure 1 will connect the user and the cloud server using the hybrid optimization algorithm.

### A. Block Diagram

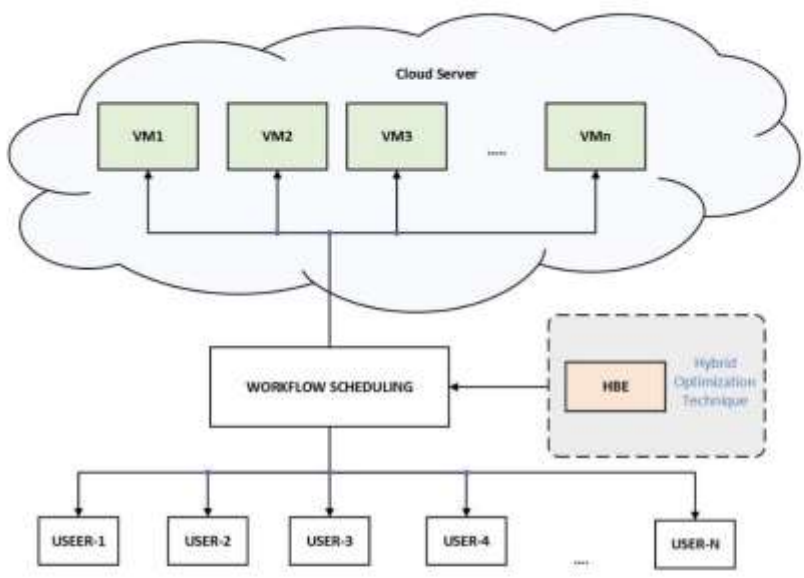


Figure 1 Block diagram for workflow schedule using hybrid optimization technique

## B. Parameters Considered

In the parameters considered section, from the server side the different parameters are the RAM allocated for the user, Memory allocated to the user, Cost for the usage. In the user side various parameters considered are the complexity of the code, and the priority of the user. All these parameters are considered to perform the optimization process.

Based on the Optimization process the different virtual machines are connected to the different users and the figure 2 given below shows the connectivity diagram for the cloud servers and the virtual machines.The weights or the complexity assigned by the user is considered to Tasks represent reference execution time, i.e., the time it takes to complete a task on a particular processor type. The average of these times are used to predict which connection type will be used by which process.

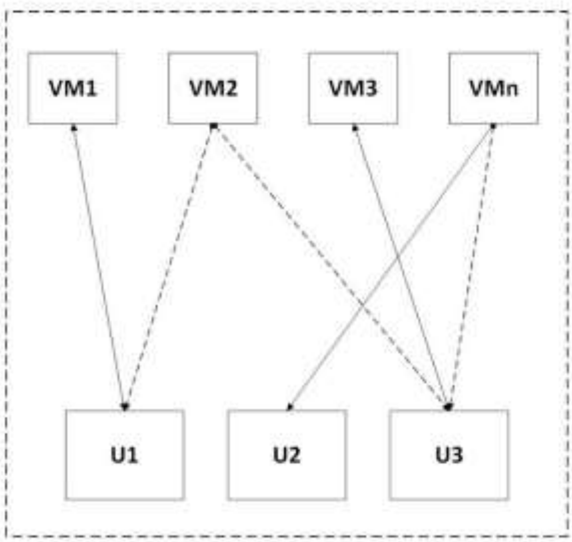


Figure 2 Connectivity between user and virtual machine

## C. Hybrid bacterial evolutionary algorithm

Computing Evolution gives functional advantages to researchers facing challenging problems of optimization. Such advantages are various, including simplicity of approach, strong reaction to changing conditions, versatility, and many other aspects. In problems where heuristic solutions are not available or lead to generally unsatisfactory outcomes, an evolutionary algorithm can be implemented.As a consequence, evolutionary algorithms, especially in relation to how they can be used to solve practical problems, have recently attracted growing interest. In general, under the term "evolutionary computing" or "evolutionary algorithms" we find the areas of genetic algorithms, evolutionary techniques, evolutionary programming, and genetic programming.They all have a similar conceptual framework through the processes of selection, transformation, and reproduction for modelling the evolution of individual structures. The process is based on the success of the individual systems defined. Evolutionary algorithms (EAs) are simpler to implement in contrast to other global optimization approaches and also have sufficient solutions. The decreased cost of using the services available is another aspect.

$$\text{Cost} = \min\left(\text{C}\left(\text{ri},\text{jk}\right)\right) \text{ for } 1 \leq \text{i} \leq \text{n}, 1 \leq \text{k} \leq \text{m} \tag{1}$$

$$\text{Makespan} = \min\left(\text{Fji}\right) \text{ for ji} \in \text{J} \tag{2}$$

$$\text{Fitness Function} = \alpha\text{cost} + \beta\text{makespan} + \gamma\text{reliabilty} \tag{3}$$

where$0 \leq \alpha \leq 1, 0 \leq \beta \leq 1$ and $0 \leq \gamma \leq 1$are the weights used to determine the preferences of the fitness function components. Cost $\text{C}\left(\text{ri},\text{jk}\right)$ is the cost of the job jkit is implemented in the resource rj, and the make span is the time it takes to complete the job.

Chemo taxis: If the movement of different bacteria tumbles over a period of time. The $x^{th}$ bacterium at the reproductive and $t^{th}$ elimination and dispersal stage of $q^{th}$ chemotactic $r^{th}$ is given by alphaα $^{x}$(q,r,t). The tumble phase size is indicated by S (x). The computation chemo taxis are described as:

$$\alpha^{x}(q+1,r,t) = \alpha^{x}(q,r,t) + S(x) \tag{4}$$

**Swarming**:Bacteria can be transferred to nutrients, so they can either be drawn to them or rejected. Only the bacterium can be attracted to specific stress periods.

**Reproduction**: After chemotaxis, the next process is regeneration. In this process, the bacteria's fitness value is determined. In ascending order, the fitness value is arranged. Unhealthy bacteria may die to preserve the size of the cluster.Healthy bacteria then divide into two. Elimination and distribution: Elimination and dispersal processes are used to eliminate local optima.The parameter used by the BEA algorithm: d is the size of the search area, N is the number of bacteria in the search area, $N_c$ is the chemotaxis step, $N_s$ is the swimming length, $N_{re}$ is the number of propagation stages, and $N_{ed}$ is the number of excretion cases. , $P_{ed}$ is the potential for exclusion-acceleration, S (i): the size of the step taken in an irregular direction.

## III. RESULTS AND DISCUSSION

The Proposed Optimal Workflow Scheduling in Cloud Computing Based on Hybrid Bacterial Evolutionary and Bees Mating Optimization Algorithm is implemented in MATLAB2019a. Performance of the Optimization is measured based on the schedule length ratio and speedup. Graphical representation of results shows that the proposed Hybrid Bacterial Evolutionary and Bees Mating Optimization methods performs more than the traditional method (GA).

Table 1 **Simulation Parameters**

| | |
|---|---|
| Number of task (n) | 10 – 100 |
| Maximum iteration | 100 |
| Objective function type | Minimum |
| Population vectors | 20 |

We are motivated by general performance comparison criteria based on design time to determine the efficacy of the proposed algorithm: schedule length ratio (SLR), acceleration.The parameters for the simulation used in the work are shown in table 1. The schedule length ratio in a schedule is the primary indicator of the algorithm for scheduling. It shall be determined by

$$\mathrm{SLR} = \frac{\text{makespan}}{\sum_{t_i \in CP_{min}} \min_{P_j \in CP_{Min}} \{w_{i,j}\}} \quad (5)$$

The denominator is the sum of the minimum computational costs of the tasks of 'CP'$_{min}$. No less than one should be the SLR of a line. In performance terms, the best algorithm is the one with the lowest SLR. By dividing the continuous execution time by the parallel execution time, the algorithm tests the speed.

$$\mathrm{Speedup} = \frac{\min_{P_i \in P} \{\sum_{t_i \in T} w_{i,j}\}}{\text{Makespan}} \quad (6)$$

Makespanis the distance in time that elapses from the start of work to the end of the work.By assigning all tasks to one processor, continuous execution time is determined.

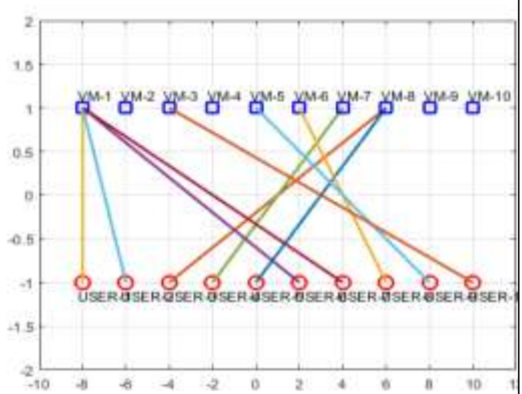


Figure 3 Network simulation diagram of user and cloud server.

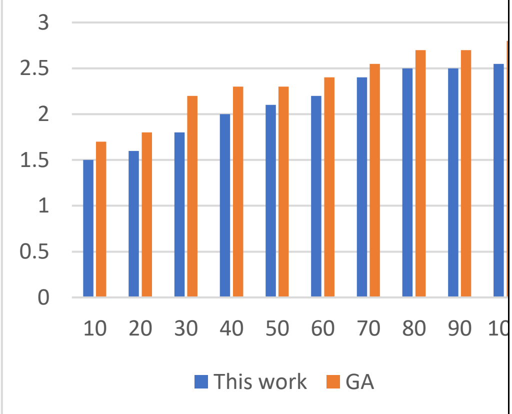


Figure 4 comparison of performance with GA

Figure 3 shows the network simulation diagram for the cloud server and the user. In the figure 4 the comparison between the execution of the proposed optimization algorithm and the GA are plotted in bar chart.

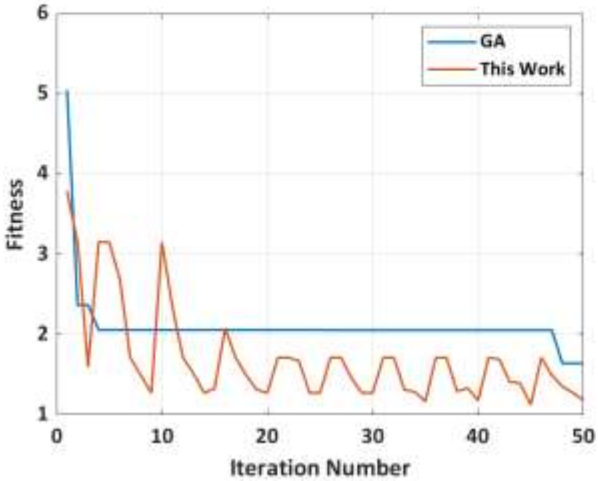


Figure 5 Performance graph of fitness function

Figure 5 shows the performance graph for the fitness function and this is plotted for the number of iterations and against the fitness value.

## IV. CONCLUSION

In this work, a new technique for workflow scheduling is proposed using hybrid optimization techniques. The proposed system is tested with various virtual machines to evaluate the performance. The fitness value is evaluated based on various cost functions which are related with computational time and cost. To evaluate the performance, various performance evaluation metrics are used. From compared to the conventional techniques, Proposed technique achieved highest performance with respect to varying number of virtual machine and service requests.

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