Independent Job Scheduling by Fuzzy C-Mean Clustering and an Ant Optimization Algorithm in a Computation Grid

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Abstract—Grid computing is gaining more significance in the high-performance computing world. This concept leads to the discovery of solutions for complicated problems regarding the diversity of available resources among different jobs in the Grid. However, the major problem is the optimal job scheduling for heterogeneous resources, in which each job needs to be allocated to a proper grid’s node with the appropriate resources. An important challenge is to solve optimally the scheduling problem, because the capability and availability of resources vary dynamically and the complexity of scheduling increases with the size of the grid. This paper, therefore, presents a framework which combines the Fuzzy C-Mean clustering with an Ant Colony Optimization (ACO) algorithm to improve the scheduling decision when the grid is heterogeneous. In the proposed model, the Fuzzy C-Mean algorithm classifies the jobs into appropriate classes, and the ACO algorithm maps the jobs to the appropriate resources. The ACO is characterized by ant-like mobile agents that cooperate and stochastically explore a network, iteratively building solutions based on their own memory and on the traces (pheromone levels) left by other agents. The simulation is done by using historical information on jobs in a grid. The experimental results show that the proposed algorithm can allocate jobs more efficiently and more effectively than the traditional algorithms for scheduling policies.

Index Terms—Fuzzy C-Mean, ACO, Job Scheduling.

I. INTRODUCTION

In high-throughput computing, the grid is used to schedule the independent jobs with respect to the dynamically distributed resources [1]. Grid computing is the principle of sharing the computational resources like processors, storage, network & instruments in a secure way. Under this principle, grid computing has faced a lot of problems in acquiring flexible, secure, and coordinated sharing among dynamic collections of resources [1, 3]. The main objective of the scheduler is to maximize the resources utilization. The previous research on scheduling for distributed systems, such as clusters and supercomputers, focused on extracting the maximum throughput from the entire system [4, 5]. Grid scheduling is responsible for resources discovery, resources selection, and job assignment over distributed nodes of the grid. Grid scheduling concentrates on improving response times in a grid containing autonomous resources whose availability varies dynamically with time. The grid scheduler must interact with the local schedulers managing computational resources and must adapt its behavior to the changing resources loads. Thus the scheduling is conducted from the perspective of the application or the user rather than that of the system. Grid scheduling involves a series of challenging tasks. These include: searching for resources in the collection of geographically distributed nodes; and making scheduling decisions according to the required quality of service. A grid scheduler differs from a scheduler for conventional computing systems in several respects. One of the primary differences is that the grid scheduler does not have full control over the grid. More specifically, the local resources are generally controlled not by the grid’s scheduler, but by the local scheduler. Another difference is that the grid scheduler cannot assume that it has a global view of the grid. The demand for scheduling is to achieve high-performance computing. It is very difficult to find an optimal resource allocation for specific jobs that minimizes the scheduled length of the jobs. The scheduling problem is a NP-hard problem [6] and it is not trivial.

There are basically two approaches to solve this problem. The first is based on job characteristics, and the second on a distributed resources discovery and allocation system. We have studied the feasibility and the usefulness of applying heuristics and machine learning techniques to this field. We provide a scheduling model [Figure 1] based on Fuzzy C-Mean (FCM) clustering and Ant Colony Optimization (ACO) algorithm for grid scheduling. In this paper, we compare our algorithm with the performance of various job-scheduling algorithms in grid computing environment.

This paper is organized as follows. Section II reviews relevant research. Section III gives a brief overview of FCM clustering and ACO algorithm. Section IV discusses problem description. Sections V and VI present some theoretical aspects of the proposed algorithm. Section VII and VIII discuss the experimental setup and results. Our conclusion and suggestions for future work are given in Section IX.

II. RELATED WORK

In grid computing, there are a lot of important issues, including job scheduling, information service, information security, resource management, routing, and fault tolerance. The job scheduling is a major problem, since it is a fundamental and crucial step in achieving high performance. Job scheduling has been described as a combinatorial
optimization problem. Scheduling in a grid can be seen as an extension to the scheduling problem on local parallel systems. In general, job scheduling predictions in a grid are dependent on the job’s execution time and the job’s running time. For example, the prediction engine module in [7] is a part of the scheduler and offers a history-based approach for estimating the run time of job submission.

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The authors in [8] proposed two modules for predicting the completion time of jobs in a service grid and for applying evolutionary techniques to job scheduling. The problem of estimating a job’s run time from historical data has been studied in [9, 10, 11]. All of them adopt the method of making predictions for future jobs by applying different job characterizations to classify similar previous jobs and then using them to make predictions. After detailed analysis, we noticed that those methods have unclear definitions of jobs, i.e. what are the important features used in measuring the similarity of jobs which can be included in the prediction module. Another approach to predict application performance and to detect of unexpected execution behavior has been proposed in [12]. These authors found that the unexpected execution behavior is typically caused by an unanticipated load on the shared grid resources. Similar predicting application’s performance on a given parallel system has been the most widely studied in [13, 14]. More recently those studies have been extended to distributed systems [15, 16, 38, 39, 40].

Traditional performance prediction techniques often focus on performance models that are specific to a single architecture or a static set of resources. However, computational grid environments consist of a collection of dynamic, heterogeneous resources and a collection of different jobs. Our approach especially examines the implications of the fact that the characterization of jobs is expected to affect the mentioned resource utilization. Even more interestingly for researchers on performance quality. We use information about static workload data from the standard workload archive [17] and from experiments reported in several publications [18, 19, 20, 21]. Moreover, these workload traces were used for the evaluation of different scheduling strategies for parallel systems [22, 23, 24, 25] and for grid research [26, 27, 28, 29, 30]. These workload traces consist of information about all job submissions on a node for a certain period of time which usually ranges over several months and several thousands of jobs. Therefore, it is reasonable to start with the available workload traces information from the computing centers to evaluate the impact of jobs characterization in grid. Our approach separated the workload data into three classes based on job run-time historical data [Figure 1]. Other algorithms such as Min-Min, Max-Min, Fast greedy Tabu search and Ant system are some of the heuristic algorithms which create a static environment. They must predict the execution time and workload in advance. In [31], the authors have proposed a simple grid simulation architecture using ACO. They used the response time and the average utilization of resources as the evaluation index. In [32] and [33], the authors proposed ACO algorithms, such as job finishing ratio which could improve the performance.

**III. OVER VIEW OF FCM AND ACO ALGORITHMS**

**A. Fuzzy C-Mean Clustering**

This paper aims to cluster jobs according to their similarities into groups. Fuzzy C-Mean (FCM) is a famous clustering algorithm for building Fuzzy partitions. FCM will be used in this approach as the basic tool for building job characterizations in grid. The FCM algorithm was introduced by Bezdek [15] as an extension to Dunn’s algorithm [16] to generate Fuzzy sets for every observed feature. Fuzzy clustering methods allow for uncertainty in the cluster assignments. Rather than partitioning the data into a collection of distinct sets (where each data point is assigned to exactly one set), Fuzzy clustering creates a Fuzzy pseudo partition, which consists of a collection of Fuzzy sets. Fuzzy sets differ from traditional sets in that membership in the set is allowed to be uncertain. A Fuzzy set is formalized by the following definitions. Let \( X = \{x_1, x_2, \ldots, x_n\} \) be a set of given data, where \( x_i \in \mathbb{R}_n \) is a set of feature data. The minimization objective function of the FCM algorithm is frequently used in pattern recognition as follows:

\[
\min_{U, V} J_c(U, V) = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^m D_{ij}^2
\]

\[
\sum_{j=1}^{c} u_{ij} = 1, \forall j, \quad i = 1, 2, \ldots, n, \quad j = 1, 2, \ldots, c
\]

\[
D_{ij}^2 = ||x_i - v_j||_2
\]

Where \( m \) is any real number > 1, \( V = \{v_1, v_2, \ldots, v_c\} \) are the cluster centers. \( U = \{uij\} \) is the degree of membership of vector \( x_i \) in cluster \( k \). The value of \( U \) must satisfy the condition in equation (3). \( D_{ij} \) is the norm Euclidean distance expressing the similarity between any measured data and the center. The cluster centers \( V \) can be calculated according to the following equations:

\[
v_j = \left( \sum_{i=1}^{n} u_{ij}^m x_i \right) / \left( \sum_{i=1}^{n} u_{ij}^m \right), \quad \forall j, \quad j = 1, 2, \ldots, c
\]

\[
u_{ij} = \left[ \sum_{k=1}^{c} \frac{D_{ik}^2}{D_{ij}^2} \right]^{-1/n}, \quad \forall i, j
\]

The algorithm will stop if \( E = ||V_i - V_{i-1}|| < T \), where \( T \) is the termination threshold and \( k \) is the iteration number.

**B. Ant Colony Optimization Algorithm**

The ACO algorithm is based upon a heuristic approach and on the behavior of real ants. Each ant deposes the chemical pheromone on its path when it searches for food from its nest. When each ant moves in a particular direction,
the strength of the pheromone increases. With this guidance, other ants can also trail along. This idea inspired the discovery of the ACO algorithm. This algorithm uses a colony of artificial ants that behave as cooperative agents in a mathematical space, where they are allowed to search and reinforce pathways (solutions) in order to find the optimal ones. This approach, which is population-based, has been successfully applied to many NP-hard optimization problems. The ACO is characterized by ant-like mobile agents that cooperate and stochastically explore a network, iteratively building solutions based on their own memory and on the traces (pheromone levels) left by other agents. At regular intervals, a forward ant is launched from a random source node to another random destination node. In its trip, the forward ant will select the next processor using a random scheme that accounts the path selection probabilities, given by the pheromone levels in each neighbor link, and a heuristics value, calculated from the congestion of each neighbor links.

IV. PROBLEM DESCRIPTION

Grid computing is dynamic that it allocates the jobs to the resources effectively. The main aim of the scheduler in the grid is to allocate the jobs to the available nodes with the best available resources. The best match must be allocated from the list of available jobs and from the list of available resources. The selection is based on the prediction of the computing power of the resource [34]. The grid users expect to run their jobs efficiently. The efficiency depends upon two criteria: makespan and flow time. These two criteria are very important in the grid system. Makespan measures the throughput of the system, and flow time measures its QoS [35]. The expected Execution Time (ET) is the expected time to complete the job. This also includes the submit time of each job. The element ET<sub>ij</sub> of the ET matrix is defined as the amount of time taken to complete the ith job on the jth resource. The jobs are owned by different users, and all jobs are interdependent. All the resources may be dynamically added or removed from the grid. They use the expected time to compute ET in [36]. The ET matrix will have N x M entries, where N is the number of independent jobs to be scheduled and M is the number of resources currently available. In our experiment, processors are taken as resources. The Ready time (Ready<sub>ai</sub>) indicates the time in which the resource ‘m’ would have finished the previously assigned jobs. The completion time of the j<sup>th</sup> job on the i<sup>th</sup> processor/resource is:

\[
CT_{ij} = Ready_{ij} + ET_{ij}
\]  

Max (CT<sub>ij</sub>) is the makespan of the complete schedule. Makespan is used to measure the throughput of the grid system. The main objective of this algorithm is to minimize the makespan. In general the existing heuristic mapping can be divided into two categories: on-line mode and batch mode. In the on-line mode, the scheduler is always ready. Whenever a new job arrives to the scheduler, it is immediately allocated to one of the existing resources required by that job. Each job is considered only once for matching and scheduling. In the batch mode, the jobs and resources are collected and mapped at a prescheduled time. The batch mode produces better decisions because the scheduler knows the full details of the available jobs and resources. The proposed algorithm is also a heuristic algorithm for the batch mode. The result of the algorithm will have four values (task, node, starting time, expected completion time). The number of jobs available for scheduling is always greater than the number of nodes available in the grid. The node M<sub>j</sub> free time will be known by using the function free (j). The starting time of job t<sub>i</sub> on resource M<sub>j</sub> is:

\[
B_i = \text{free} (j) + 1
\]  

Then the new value of free (j) is the starting time + ET<sub>ij</sub>. In the algorithm, the minimization function is used in order to find out the best resource:

\[
F = \max \text{ (free} (j))
\]  

And use the following heuristic information is used:

\[
\eta = 1 / \text{free} (j)
\]  

Formula # 9 is used to find out the highest priority node which is free earlier. All the ants are maintaining a separate list. Whenever they select the next task and resource, they are added into the list. The ants calculate the minimize function for ‘F<sub>i</sub> (k<sub>a</sub> ant)’ and the pheromone trail updates the value:

\[
\Delta T_{ij} = 1 - p / F_i
\]  

In this algorithm, two set of tasks are maintained: the scheduled tasks and newly arrived & unscheduled tasks. The algorithm starts automatically, whenever the set of scheduled jobs become empty. According to [37], the first task to be performed, and the machine in which it is performed are chosen randomly. Next, the task to be run and the node in which it is to be run are computed by the following formula:

\[
P_j = T_j, \eta, \Sigma T_{ij} - \eta
\]  

- \( \eta \) is the attractiveness of the move as computed by some heuristic information indicating a prior desirability of that move;
- \( T_{ij} \) is the pheromone trail level of the move, indicating how profitable it has been in the past to make that particular move;
- \( P_j \) is the probability to move from a state i to a state j depending on the combination of the above two values.

V. THEORETICAL ANALYSIS

The goal of the proposed scheduling algorithm is to minimize the total execution time of jobs. As the scheduling is performed statically, all necessary information about the jobs in the grid and the processors in the system is assumed to be available a priori. For the heterogeneous environment, we used a hybrid approach in which grouping of jobs is done using FCM clustering algorithm and affinity between jobs and processors is calculated using ACO algorithm. Essentially, the expected running time of each job on each processor must be known, and this information can be stored in an expected ET matrix. A row in an ET matrix contains the ET for a single job on each of the available processors, and so any ET matrix will have n x m entries, where n is the number of jobs and m is the number of resources or processors. In order to simulate various possible heterogeneous scheduling problems as realistically as possible, we define different types of ET matrix for our experiments: execution time, submission time, load balancing and fault tolerance. The task heterogeneity in our experiment is defined as the processors are not identical, and each processor can take a differing amount of time to process any given job with respect to available resources.

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A. Finding Job Clusters

In our approach FCM clustering algorithm is used as the basic tool for building jobs characterization in grid environment. Initially, we have given unlabeled dataset of jobs represented by \( X = \{x_1, x_2, x_3, \ldots, x_n\} \) where \( n \) is the number of jobs in \( X \). Also each \( x_k \in X \) is defined as \( x_k = (v_1, v_2, \ldots, v_p) \) where \( p \) is the number of features in each input vector. For our approach we used completion time, submission time and resources required as features. As far as clusters are concerned, we used three clusters of jobs as heavy, medium and small workload. They are represented as \( V = \{v_1, v_2, v_3\} \) \( \epsilon \) \( Rp \) where \( v_i \) is the \( i \)th cluster center. After the initialization, next step is the calculation and optimization of objective function represented in equations (1, 2, 3 and 5). The objective function represents the degree of membership value of each job against each cluster and is calculated by using Euclidean distance. The cluster centers are calculated by using aggregated mean represented in equation (4). The cluster centers are updated in every iteration, and the algorithm continues until \( E = \sum_{i=1}^{k} \|x_i - v_i\| < T \), where \( T \) is the termination threshold, and \( k \) is the iteration number. After that, these workloads are sent to the ACO algorithm for optimization.

B. Defining the Pheromone Trial

The fact that jobs will run at different speeds on different processors means that this problem cannot be approached as the same sort of grouping problem as for the homogeneous case. However, we can exploit this fact to use what is perhaps the more intuitive pheromone trail definition that certain jobs may have certain affinities with certain processors, and so it would be useful to store information about good processors for each job. The pheromone value \( T_{ij} \) is selected to represent how profitable is to schedule a particular job \( i \) onto a particular processor \( j \). For the first time, all processors have value 0.5, means every job has the same benefit or 50 percent profit running on any processor. After the heuristic and the fitness functions are calculated to produce the final pheromone matrix. The pheromone matrix will thus have a single entry for each job-processor pair in the problem.

C. The Heuristic and Fitness Functions

The min-min heuristic is a very effective algorithm for this problem. It suggests that the heuristic value of a particular job should be proportional to the minimum completion time of the job, that is the time a job \( i \) can be expected to finish on a processor \( j \). Contrary to conventional ACO algorithm which was using only one ant for heuristic and fitness function, we are calculating probability matrix \( (P_{ki}) \) by using \( k \) ants. The minimum completion time of a job \( i \) on a processor \( j \) is used for the heuristic function. The resulting \( \eta_{ij} \) function value by the ants is defined in equation (9). If the job \( i \) has minimum completion time on processor \( j \), then by using \( \eta_{ij} \) for calculating probability in equation (11), we can find the best processor \( j \) for that job \( i \) which can complete job \( i \) in minimum time span. The same procedure is done by each ant having their own heuristic and fitness function values.

D. Updating the Pheromone Value

For updating the pheromone value, ants should be allowed to share information about good solutions for a policy. Allowing only the best ant to leave pheromone after iterating makes the search much more aggressive, and significantly improves the performance of ACO algorithms. Using equations (10, 11), each ant follows the same pheromone update policy for each pair of job \( i \) and processor \( j \) in their own pheromone matrix.

\[
T_{ij} = \rho T_{ij} + \gamma T_{ij}
\]

Where \( \rho \) is a parameter which defines the pheromone evaporation rate and \( \gamma \) is the pheromone trial value.

E. Building a Solution

A simple strategy, following the minimum execution time approach, would be to allocate each job \( i \), in arbitrary order, to a processor \( j \) picked probabilistically with respect to the pheromone value between \( i \) and \( j \), and the execution time of completion of \( i \) on \( j \) (a lower value is preferable). The solution building technique used for this ACO approach is an attempt to follow the concept of the best heuristic method. First, the processor \( j \) which completes a job \( i \) earliest is established. A job \( i \) then picked to be scheduled next based on the pheromone value between job \( i \) and processor \( j \). The probability of selecting job \( j \) to be scheduled next is given by equation (11). At this stage, we have \( k \) probability matrices one for each ant. A job is then selected based on the highest probability among all the matrices, and the chosen job \( i \) is then allocated to processor \( j \). This process is repeated until all jobs have been scheduled and a complete solution has been built.

In [37], the algorithm uses only one ant. To overcome this disadvantage, a new algorithm is proposed. In this method, the probability matrix \( (P_{ki}) \) is modified by using several ants \( (k \) ants) and the number of ants used is less than or equal to the number of tasks. From all the possible scheduling lists, the one having the minimum makespan is found and that ant’s scheduling list is used. So, at the time of execution, the scheduler finds the list of available resources (processors) in the grid, forms the ET matrix, and starts scheduling. The steps for the proposed algorithm are as follows:

1. Find the classification of workload by FCM clustering.
2. Collect all necessary information of jobs \( n \) and resources \( m \) of the system in the ET matrix and the submit Time matrix (size should be \( m \times n \)).
3. Set all the initial values, \( \rho = 0.05 \) (pheromone evaporation value), \( T = 0.5 \) (initial pheromone deposit value), \( \text{Free} = 0 \) (one dimensional matrix of size \( m \)), \( k = m \) (\( k \) is the number of ants, and \( m \) is the number of resources).
4. For each ant (to prepare the scheduling list) do the steps # 5 and 6.
5. Select the task \( i \) and resource \( j \) randomly.
6. Repeat the following until all jobs are executed.

a. \( \eta_{ij} = 1 / \text{Free}(j) \)
b. Calculate the pheromone trail value \( \Delta T_{ij} = 1 - \rho / F_k \), where \( F_k = \max(\text{free}(j)) \)

c. Update the pheromone trail matrix \( T_{ij} = \rho \cdot T_{ij} + \Delta T_{ij} \)

d. Calculate the Probability Matrix \( P_{ij} = T_{ij} \cdot \eta_{ij} / \sum T_{ij} \cdot \eta_{ij} \)

e. Select the highest probability \( i \) and \( j \), (the next task \( i \) to be executed on resource \( j \))

7. Find the best feasible solution by using the scheduling list of all the ants. Best feasible solution leads to the minimum makespan time of nodes and to the minimum average waiting time of jobs.

Load balancing and fault tolerance are checked during runtime. If any load is overloaded, jobs are swapped from one node to another. Also, if any node fails, all the remaining jobs are distributed among other nodes.

VI. EXPERIMENTAL SETUP AND RESULTS

In the experiments, we used a workload data from a standard workload archive [17]. These data consists of 1,000 jobs, from which 500 are randomly selected for the experiment. Each job’s record has 18 attributes. However, we focused on the execution time and submission time of each job. In the experiments we assumed that each job is allowed to run in each node by using a space-sharing mechanism. In the space-sharing mechanism, each processor can serve only one job at a time. We simulated 10 different performance nodes in the grid. The experiments were conducted in five parts. The first part focused only on the execution time of jobs and all the remaining parts treat both execution and submission time. The second part took care of the execution time as well as the submission time of jobs. The third part supports load balancing between the nodes, the fourth part of the experiment supports fault tolerance and the fifth part focused on the affect of the number of users. The experiments showed the classification of jobs workload into three groups: heavy, medium and light workload (Figure 2). Figure 3 shows the job membership functions given by using FCM clustering algorithm.

In the experiments, the jobs in workload data are allocated to three classes, each with number of jobs shown in Table 1. After classifying of the workload, the workload is given to the proposed ACO algorithm for grid scheduling. In our experimental testing, we used 10 heterogeneous nodes and 500 tasks. For the performance measure, we evaluated the completion time of each node along with the waiting time of each individual job. We compared the results of the ACO algorithm with the three traditional job scheduling algorithms: First-Come-First-Served (FCFS), Largest Job First (LJF) and Shortest-Job-First (SJF).

### Table 1: Workload Classes

<table>
<thead>
<tr>
<th>No</th>
<th>Class</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Heavy Job Workload</td>
<td>72</td>
</tr>
<tr>
<td>2</td>
<td>Medium Job Workload</td>
<td>66</td>
</tr>
<tr>
<td>3</td>
<td>Small Job Workload</td>
<td>362</td>
</tr>
</tbody>
</table>

![Figure 2: (a) Pool of Jobs (b) Separate Clusters of Job](image1)

![Figure 3: Membership Function of Workload](image2)
A. Jobs with Execution Time only

The results for the first time, where we consider only the execution time of job are shown in Figures 4 and 5. In Figure 4, we can see that all the nodes have minimum completion time when using the ACO algorithm as compared to others. This completion time includes the execution time and the waiting time of all jobs at their nodes. Similarly, Figure 5 shows that nearly all the jobs have less waiting time than SJF, LJF and FCFS.

![Completion Time of each Node when only the Execution Time is considered](image1)

**Figure 4: Completion Time of each Node when only the Execution Time is considered**

B. Jobs with Execution and Submission Time

For this case, we include the submit time of each job when they arrived. So the total waiting time of each job contains the execution time of all previous jobs plus the time from its submission to the time when it gets a processor. The results are shown in Figures 6 and 7. We can conclude that SJF and the proposed ACO algorithms have similar completion times as compared to other algorithms when the submission time is considered.

![Completion time of each Node when the Execution and the Submission Time are considered](image2)

**Figure 6: Completion time of each Node when the Execution and the Submission Time are considered**

C. Load Balancing between Nodes

We implemented a load-balancing mechanism between all nodes. The proposed algorithm continuously monitors each node, and, if any node becomes overloaded, the jobs are migrated from one node to another. The results are shown in Figures 8 and 9. We can see that all the algorithms are trying to balance the load at each node, and here our proposed algorithm ACO has the minimum completion time for each node.

![Waiting time for each job](image3)

**Figure 5: Waiting Time for each job when only the Execution Time is considered**

![Waiting time for each job](image4)

**Figure 7: Waiting Time for each job when the Execution and the Submission times are considered**

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D. Fault Tolerance

We considered a scenario in which node 4 failed after some time. In order to support fault tolerance, jobs on node 4 are distributed between different nodes taking care of the completion time as well as the load balancing using checkpoint-restart during runtime. The results are shown in Figures 10 and 11. We can see that the proposed ACO algorithm outperforms all other algorithms despite the failure of nodes. The overall results are stated in Table 2, which shows that the proposed ACO algorithm performs best among different algorithms under different circumstances.

### Table 2: Completion Time for Each Node in Different Scenarios

<table>
<thead>
<tr>
<th></th>
<th>FCM+ACO Algorithm</th>
<th>SJF</th>
<th>LJF</th>
<th>FCFS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Execution time only</td>
<td>75.1533</td>
<td>272.137</td>
<td>495.316</td>
<td>405.863</td>
</tr>
<tr>
<td>Execution + Submission times</td>
<td>988.7</td>
<td>1274.5</td>
<td>2990.1</td>
<td>2313.8</td>
</tr>
<tr>
<td>With Load Balancing Mechanism</td>
<td>838.4</td>
<td>1319.9</td>
<td>1659.2</td>
<td>1640.9</td>
</tr>
<tr>
<td>With Fault Tolerance Mechanism</td>
<td>1012.8</td>
<td>1663.4</td>
<td>3488.7</td>
<td>2697.2</td>
</tr>
</tbody>
</table>

Figure 8: Waiting Time of each job by using Load Balancing Mechanism

Figure 9: Waiting Time for each Node using Load Balancing Mechanism

Figure 10: Waiting Time for each Node when one Node Fails

Figure 11: Waiting Time of each job when one Node Fails
VII. EXPERIMENT WITH THE NUMBER OF USERS

We carried out another experiment based on the number of users with four different cases. The number of users is defined by three different configurations as shown in Table 3. For 10 users, the completion time for each scheduler with respect to four different scenarios is stated in the Table 4. For 25 users, the completion time for each scheduler with respect to four different scenarios is stated in the Table 5. For 50 users, the completion time for each scheduler with respect to four different scenarios is stated in the Table 6. From Figures 12, 13, and 14 we can infer that the proposed algorithm performs better than all the traditional scheduling algorithms. With the proposed algorithm, the completion time for all jobs is less for all user configurations as well as for all different scheduling algorithms. Also as the number of users and number of jobs increases, the proposed algorithm is performing much better than the traditional scheduling algorithms. For 10 users’ configuration, the difference between the completion time of FCM-ACO algorithm and SJF is small, but for 50 users’ configuration, the difference between the two algorithms increased. This shows that in real time environment where we have a huge number of users, the proposed algorithm will definitely perform better as compared to others scheduling algorithms.

TABLE 3: NUMBER OF USERS & JOBS IN DIFFERENT SCENARIOS

<table>
<thead>
<tr>
<th>Number of Users</th>
<th>Jobs per User</th>
<th>Total Number of Jobs</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>10</td>
<td>100</td>
</tr>
<tr>
<td>25</td>
<td>10</td>
<td>250</td>
</tr>
<tr>
<td>50</td>
<td>10</td>
<td>500</td>
</tr>
</tbody>
</table>

TABLE 4: COMPLETION TIME FOR 10 USERS

<table>
<thead>
<tr>
<th></th>
<th>FCM+ACO</th>
<th>SJF</th>
<th>LJF</th>
<th>FCFS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Execution time only</td>
<td>17.04</td>
<td>46.76</td>
<td>279.17</td>
<td>144.96</td>
</tr>
<tr>
<td>Execution time + Submission time</td>
<td>52.753</td>
<td>95.69</td>
<td>423.04</td>
<td>398.88</td>
</tr>
<tr>
<td>With Load Balancing Mechanism</td>
<td>21.319</td>
<td>40.292</td>
<td>860.14</td>
<td>749.38</td>
</tr>
<tr>
<td>With Fault Tolerance Mechanism</td>
<td>206.73</td>
<td>250.67</td>
<td>1143.3</td>
<td>1258.4</td>
</tr>
</tbody>
</table>

TABLE 5: COMPLETION TIME FOR 25 USERS

<table>
<thead>
<tr>
<th></th>
<th>FCM+ACO</th>
<th>SJF</th>
<th>LJF</th>
<th>FCFS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Execution time only</td>
<td>43.23</td>
<td>244.80</td>
<td>366.12</td>
<td>300.75</td>
</tr>
<tr>
<td>Execution time + Submission time</td>
<td>32.48</td>
<td>104.96</td>
<td>512.10</td>
<td>280.12</td>
</tr>
<tr>
<td>With Load Balancing Mechanism</td>
<td>129.05</td>
<td>230.62</td>
<td>552.06</td>
<td>381.26</td>
</tr>
<tr>
<td>With Fault Tolerance Mechanism</td>
<td>122.60</td>
<td>208.52</td>
<td>444.82</td>
<td>385.27</td>
</tr>
</tbody>
</table>

TABLE 6: COMPLETION TIME FOR 50 USERS

<table>
<thead>
<tr>
<th></th>
<th>FCM+ACO</th>
<th>SJF</th>
<th>LJF</th>
<th>FCFS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Execution time only</td>
<td>75.15</td>
<td>272.13</td>
<td>495.31</td>
<td>405.86</td>
</tr>
<tr>
<td>Execution time + Submission time</td>
<td>988.7</td>
<td>1274.5</td>
<td>2900.1</td>
<td>2313.8</td>
</tr>
<tr>
<td>With Load Balancing Mechanism</td>
<td>838.4</td>
<td>1119.9</td>
<td>1659.2</td>
<td>1640.9</td>
</tr>
<tr>
<td>With Fault Tolerance Mechanism</td>
<td>1012.8</td>
<td>1663.4</td>
<td>3488.7</td>
<td>2697.2</td>
</tr>
</tbody>
</table>

Figure 12: Completion Time for 10 Users

Figure 13: Completion Time for 25 Users

Figure 14: Completion Time for 50 Users
VIII. CONCLUSION AND FUTURE WORKS

We have studied the job scheduling for a grid environment as a combinatorial prediction and optimization problem. We have proposed an intelligent scheduling algorithm in a grid which uses the FCM clustering technique for predicting three classifications of job workload and the ACO algorithm for allocating them to different grid nodes. The proposed hybrid scheduling is very efficient in terms of calculation, because classifying the workload in the first step made the calculation very simple for the ACO algorithm, and it can efficiently schedule each job with respect to its workload class. The experimental results, for each part on the completion time of nodes and the waiting time of each job have shown that the scheduling system using the proposed algorithm outperforms all other algorithms and gives optimal results. Also, from all the traditional scheduling algorithms, only SJF is comparable to the ACO algorithm. Also as the number of users and number of jobs increases, the proposed algorithm is performing much better than the traditional scheduling algorithms. For future work, our simulation environment will include more complex characterization of the constraints for grid scheduling in real time systems.

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REFERENCES


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