Multi-objective Evolution based Dynamic Job Scheduler in Grid

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by

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CERTIFICATE

It is certified that the work contained in this thesis entitled "*Multi-objective Evolution based Dynamic Job Scheduler in Grid*", by *Debjyoti Paul(Roll No. 11111015)*, has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

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Abstract

Grid computing is a high performance computing environment to fulfill large-scale computational demands. It can integrate computational as well as storage resources from different networks and geographically dispersed organizations into a high performance computational & storage platform. It is used to solve complex computational-intensive problems, and also provide solution to storage-intensive applications with connected storage resources. Scheduling of user jobs properly on the heterogeneous resources is an important task in a grid computing environment. The main goal of scheduling is to maximize resource utilization, minimize waiting time of jobs, reduce energy consumption, minimize cost to the user after satisfying constraints of jobs and resources. We can trade off between the required level of quality of service, the deadline and the budget of user.In this thesis, we propose a Multi-objective Evolution-based Dynamic Scheduler in Grid. Our scheduler have used Multi-objective optimization technique using Genetic algorithm with pareto front approach to find efficient schedules. Our avant-garde crossover, mutation and selection operators offer exploration of search space vividly to avoid stagnation and generate near optimal solution. We propose that our scheduler provides a better grip on most features of grid from perspective of grid owner as well as user. Dynamic grid environment has forced us to make it a real time dynamic scheduler. A job grouping technique is proposed for grouping fine-grained jobs and for ease of computation. Experimentation on different data sets and on various parameters revealed effectiveness of multi-objective scheduling criteria and extraction of performance from grid resource.

Dedicated to
my parents, my sister & a special friend

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Chapter 1

Introduction

Grid computing is used to solve large scale computational problems. Grid is a type of parallel and distributed system that enables sharing, selection and aggregation of geographically distributed resources dynamically at run time depending on their availability, capability, performance, cost, user's quality-of self-service requirement [8]. The computational capabilities of grid resources can vary a lot, which are connected through internet or private networks. Grid is beyond simple communication between computers and ultimately aims to turn the global network of computer into one vast computational resource. It is a virtual computing environment having a collection of clusters, where a cluster means more than one node connected to each other either within a cabinet or over a LAN giving users a single system image [30]. A Grid has features of choosing a resource in some specific manner and submit jobs on it. It has various important facilities such as scalability, high throughput, and high performance. It facilitates large scale resource sharing resulting in high speed job execution with less cost. Thus it can be said that a grid is a hardware and software infrastructure that provides a dependable, consistent, pervasive, and inexpensive access to high performance computing resources [13].
On the basis of functionality grid can be classified as:

- **Computational Grid:** A computational grid is a collection of distributed computing resources, within or across locations that are combined to act as a

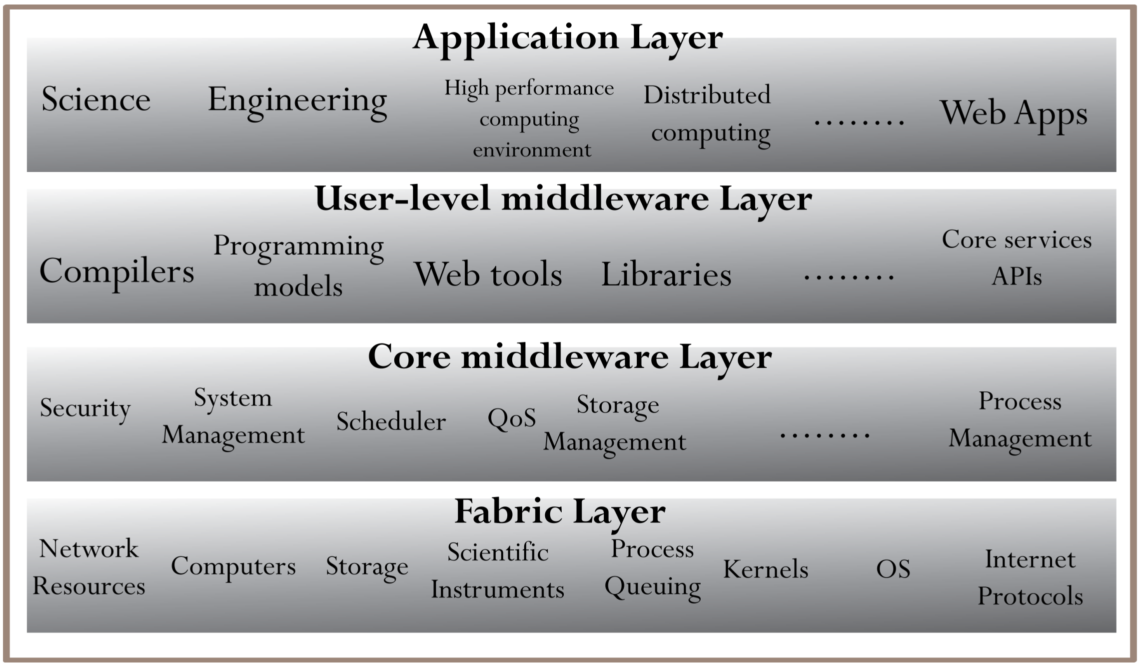


Figure 1.1: Grid Architecture and components

unified computing resource.

- **Data Grid:** Data grid primarily deals with providing services and infrastructure for distributed data-intensive applications that need to access, transfer and modify massive datasets stored in distributed storage resources [9].

1.1 Grid Architecture

Grid architecture [8] is described in layers, where each layer has some set of functions. Upper layers are application and user centric and lower layers are hardware centric. It consists of four layers i.e., application and portal layer, user-level middleware layer, core middleware layer and fabric layer. Figure 1.1 shows the stack within a grid architecture.

- **Fabric layer:** The lower layer of grid architecture consists of network components, distributed resources, storage devices etc. Computational resources represent multiple architectures such as clusters, supercomputers, servers, ordinary PCs and even PDAs.

- **Core Middleware layer:** The middleware layer is referred to as the “brains“ behind a computing grid. It provides tools for managing grid elements. It offers services like remote process management, allocation of resources, storage access, resource information registration/discovery, security, and Quality of Service (QoS).

- **User-level Middleware:** This layer helps users to build applications for grid with application development environment and various sets of programming tools. It has access to API’s provided by the core middleware layer.

- **Application layer:** This is the layer users interact with. This includes applications in engineering, science, business, finance and more. This also provide development toolkits to support the applications. Grid portals can also offer scalable web-based application services.

1.2 Grid job scheduler

Grid performance can be improved in terms of job processing time by making sure that all the resources available in the grid are utilized optimally using a good job scheduling algorithm. Job scheduler exists in many conventional distributed environment systems but in grid there are several characteristics that make the scheduling different and more challenging. Some of these characteristics are dynamic structure of the computational grid, high heterogeneity of resources, jobs and interconnection networks, existence of local policies on resources and local schedulers, the large scale of the grid system and security [39].
The grid scheduler has to follow a series of steps [28] : (1) Collecting information of jobs submitted to the grid, (2) Collecting available resource information, (3) Computation of the mapping of jobs to selected resources, (4) Jobs allocation according to the mapping, and (5) Monitoring of job completion. There are two types of scheduling :

- **Static scheduling:** Jobs are statically assigned to resources before their execution begins. The jobs can not be rescheduled or interrupted once its execution starts.

- **Dynamic scheduling:** Re-evaluation is allowed of already taken assignment decisions during job execution is allowed[11] . It can trigger job migration or interruption, based on dynamic information about the status of the system and the workload.

The Job scheduling in Grid can be correlated with a classical problem, Flexible Job-shop Scheduling problem(FJSP) [7] with dynamic changes of resources and their availability. Besides these grid jobs need to be scheduled as soon as possible after they are enqueued in the job queue, granting the scheduler only a few minutes of time to find the scheduling strategy. FJSP consists of routing subproblem and the scheduling subproblem [36]. Routing problem is to assign each job with a resource among a set of resources and scheduling problem is to obtain a feasible and satisfactory sequence of jobs within the resources.

Computationally, FJSP is as hard as JSP which is an NP Hard problem[15] . So finding near optimal solution in polynomial time is our aim. The problem becomes even more interesting when multiple objectives are there to be taken care of. Nearly all job scheduling algorithms work on single objective like makespan (classical FJSP minimize makespan only).

Finding near optimal solution for FJSP problem with more than one objective in a time efficient way is a difficult task. Grid environment being dynamic in nature, reallocation of jobs is quite evident in it.

Our approach of solving the above problem using Non-dominated sorting evolutionary algorithm for minimization of multiple objectives, is well enough to find near optimal scheduling strategy in time. The running time complexity of algorithm is $O(GMN^2)$ where G is the number of generations or iterations, M is the number of objectives and N is the population size of the chromosomes or scheduling strategies to run the algorithm.

1.3 Motivation

Grid aims at aggregating widely distributed resources and providing low cost computing resources to users. Resources can be computers, storage space, network resources connected through internet or private network with a middleware providing management capability. An Essential part of a Grid system is an efficient scheduling system i.e. resource sharing problem in dynamic and multi-institutional organizations [14]. Grid scheduling algorithms are inspected with different perspectives, such as static vs. dynamic, application models, QoS constraints, objective functions. Maximum utilization of grid resources is the most cogitated objective in scheduling literatures. However other factors like maintaining QoS constraints, cost effectiveness, energy efficient scheduling were either discussed separately or not acknowledged. Fair amount of importance should be given to user satisfaction, time and cost deadline of jobs. In 2007, Gartner estimated that the Information and Communication Technology industry is liable for 2% of the global CO_2 emission annually, which is equal to that from the aviation industry [29]. A study done at the Lawrence Berkeley National Laboratory shows that the cooling efficiency (the ratio of computing power to the cooling power) of data centers varies drastically from a low value of 0.6 to a high value of 3.5 [16].
Above mentioned facets clearly show an urgency for a multi-objective grid scheduler, dealing them on their gravity of importance.

1.4 Contribution of this thesis

We present a multi-objective Job scheduler based on an evolutionary algorithm. The aim of this work is to give grid administrators a better scheduler, which will give better grip on the trade off among cost, utilization, energy efficiency and QoS. The scheduler can cope up with the dynamic behavior of resources, resource constraints and predecessor job constraints. A job grouping mechanism is proffered for fine grained jobs.

Pareto front approach is taken in multi-objective optimization. Non-dominating sorting mechanism with avant-garde crossover and mutation operator enables the scheduler to explore the search space minutely.

Objective functions can be classified into two categories: application-centric and resource-centric. Negotiation and trade off between two types of objectives is necessary. Our generalized multi-objective scheduler provides options to add and remove objective functions.

1.5 Organization of the Thesis

The organization of the rest of the thesis and a brief outline of the chapters is as follows. In chapter 2, some related works on job scheduling in grids and their merits and demerits have been discussed. In chapter 3, Multi-objective Evolution based Dynamic Job Scheduler in Grid has been presented. Here problem definition, job-grouping strategy, problem formulation, MOJS module and algorithms are described. In Chapter 4, implementation details and experimental results are given. Chapter 5 sums up the work with conclusion and future work.

Chapter 2

Related Work

Job shop scheduling problem is at least 70 years old. Considerable effort to solve it and find computational complexity has been found to be in 1960 [26]. This has been proven to be an NP-complete problem in 1979 [21]. Many researcher have used heuristic based solving approach to address the problem. Local Search [32], Tabu search [1], simulated Annealing [40] [1] are single heuristic based approach.

In Tabu search, one solution s moves to another solution s' located in the neighborhood with a slight modification possible from s. Tabu search overcomes the local optimality with a steepest descent/mildest ascent approach. However performance of TS largely depends on the parameters and heuristic used in formulating the problem. For multi-objective scheduling TS might not be sufficient.

In simulated annealing technique, each solution is mutated and if the mutant spawned exceeds threshold it is rejected, and if less than or equal to the energy of the parent, the difference of threshold and energy of mutant is added to Energy Bank(EB). The threshold is changed when EB reaches a certain value and population moved to new generation. Simulated annealing mutation/reheating is directly proportional to the energy accumulated in EB. Simulated annealing in Multiobjective domain e.g. AMOSA [4] requires many parameters and domination factor to find near optimal solutions, which are hard to established in grid scheduling.

There are also some hybrid approaches like Tabu search with Ant colony Optimization [31] [33], GA's with Simulated annealing [42].Other predictive model approaches for the problem are Particle Swarm optimization [25] [2], Fuzzy based scheduling [22]. AI based scheduling algorithms like Max-min (Task with more computation time has higher priority), Min-min (Task with less computation time has higher priority), Suffrage (Task with higher sufferage value is given higher priority, its value is determined as the difference of computational time between best and second best resources on which job can be allocated)[19]. All the above work have focused on single objective i.e. minimizing the makespan, which in turn maximizes the utilization of resources. Resource constraint was also not taken into consideration.

Job grouping based scheduling algorithm is used for fine-grained jobs & lightweight jobs which increase the resource utilization [27] [3] . The later have considered communication and bandwidth capabilities. However they have not taken care of predecessor job completion constraint and dynamic behavior of resources in grid.

Genetic algorithms are a stochastic search method introduced in the 1970s in the United States by John Holland [Holland 76] and in Germany by Ingo Rechenberg [Rechenberg 73]. It is based on Darwin's natural selection principle of evolution of biological species. GA operate on a population of solution and apply heuristics such as selection, crossover, and mutation to find better solutions [35].

EDSA is a GAs searching technique in which the crossover and mutation rates are changed dynamically depending on the variances of the fitness values in each generation [41] . The scheduling consider minimization of makespan. MOEA has addressed the need for multi-objective minimization on computational grid, their work was limited to one type of resource, two objectives i.e. makespan & flowtime, and lacks predecessor job constraint [17].

In our work based on multi-objective evolutionary algorithm we have converted resource scheduling problem in grid into *resource-constrained project scheduling problem*. We have incorporated dynamic scheduling mechanism, advanced crossover and mutation operator & minimizing five objectives with pareto front technique. The GA structure of Non-dominating Sorting Genetic Algorithm II proposed by K.Deb *et al.* have helped us in creating the MOJS module [12].

GA based scheduler can act as a real time scheduler due to increase in computational capability of processors in last five years. We have proposed a job grouping strategy for fine-grained jobs, so that it can deliver job schedule to dispatcher on time.

A comparable work with matching constraints could not be found in literature, only few publications deal with multi-objective scheduling [17] but their platform is different from ours. So in result section we experimented our scheduler and produced result on the performance based on various parameters.

Chapter 3

Multi-objective Evolution based Dynamic Job Scheduler in Grid

3.1 Problem Definition

Grid is a distributed decentralized heterogeneous computational system, later it has also incorporated network storage system. User applications run on Grid varies from lightweight to extensive computational/storage application with various constraints. Job Scheduler is responsible to select best suitable machines in this grid for each job. In large grid this should be done automatically. The scheduling system generates job schedules for each machine in the grid by considering predefined static constraints of jobs and machines and dynamic behavior of grid. Grid environment is highly dynamic, resources can join and leave grid any time.
We define the problem in three sections as follows:

3.1.1 Flexible Job Shop Scheduling

The typical job-shop problem is formulated as a work order that consists of set of n jobs, each of which contains m tasks. Each task has predecessors and requires a certain type of resource, i.e. to be processed by any machine from a given set [35]. Often many resources of a specific type are available, for example five milling machines and two lathes. Many tasks can be assigned to any one of the available resources, but the resource must be of the suitable type. Similarly in the computing environment some computational jobs have certain requirement specifications and resource types to maintain their quality of service. Typical objectives for scheduling include minimizing the makespan for the work order. Here we are also considering energy consumption, time limit constraint, cost constraint and maximize utilization of resources as objectives.

3.1.2 Dynamic Scheduler

Dynamic scheduler considers dynamic environment of grid where resources can change its configuration and availability. In dynamic scheduling re-evaluation is allowed for already taken assignment decisions during job execution [10]. It can trigger job migration or interruption based on dynamic information about the status of the system and the workload. When a resource leaves grid system the Grid Information Service (GIS) can trigger the scheduler to reschedule the queued jobs among the available resources. However care should be taken on scheduling the jobs that are dependent on the rescheduled jobs. Similarly addition of new resources will trigger reshuffling of the jobs for proper utilization of resources though less complexities are involved in this case. Section 3.5 addresses this problem.

3.1.3 Gridlet

Grid job is often referred to as Gridlet. Jobs can be fine as well as coarse grained. In grid computing, MI is the unit of job size. MI is million instructions or processing requirements of a user job [24]. If the MI of a job is less than a fixed threshold M, it is a fine-grained job. Similar approach i.e. Megabytes(MB) parameter is used for storage intensive jobs. For fine-grained jobs, a job-grouping strategy is suggested for faster execution of scheduler in section 3.6.

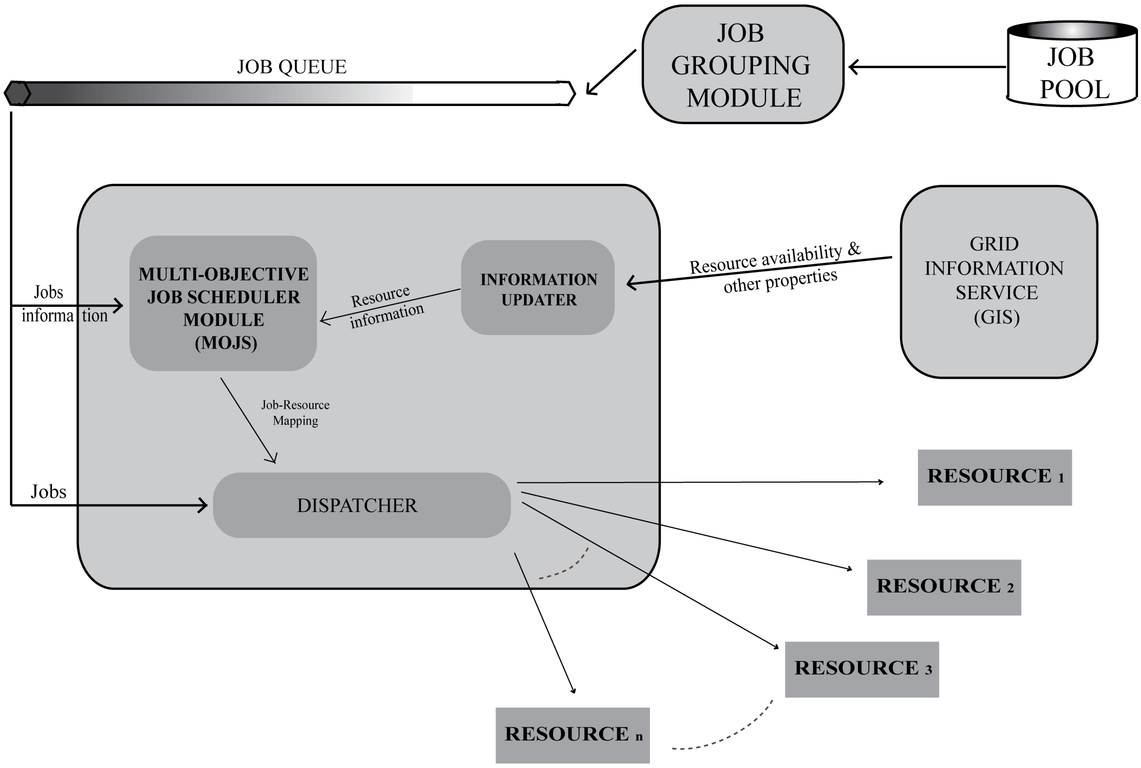


Figure 3.1: Scheduling Model

3.2 Job Scheduling Model

The four basic building blocks of grid model are as follows

- Users
- Job scheduler
- Grid Information System (GIS)
- Resources

The user submits a list of jobs to the job pool where it gets a unique identification number i.e. Job ID. If necessary job-grouping of very fine-grained jobs is accomplished by meta-scheduler before the scheduler process these jobs. The scheduler obtains information of resources from Grid Information Service (GIS). GIS provides information like resource availability, processing capability, energy consumption and cost details. Based on the information, a scheduling strategy i.e. mapping of jobs with execution start time and resources is created and send to dispatcher. The dispatcher dispatch jobs to their corresponding resources on time and collects the results of completed jobs from the resources.

3.3 Formulation of problem

Here the problem is formulated with the notations described in scheduling literature [6], [5], [20]. Given are a set $M = \{M_1, M_2, M_3, ...M_m\}$ of resources, a set $J = \{J_1, J_2, J_3, ...J_j\}$ of application jobs, and a set O of grid jobs. The n Grid Jobs of application job J_i are denoted by $O_{i1}, ..., O_{in}$, a set $W = \{W_1, W_2, \ldots, W_m\}$ denotes normalized energy dissipation factor of resources. Table 3.1 gives a concise definition of the notations have been used.

The following functions are used:

Table 3.1: Notation Symbol and their definitions

Notation	Definition
M_i	Resource with ID i
J_i	Application job with ID i
O_{ij}	jth Grid Job or task of Application job J_i
W_i	Energy dissipation factor of Resource M_i, normalized with the max value from set W
$t(O_{ij}, R_{ij})$	Processing time of O_{ij} mapped to resource R_{ij}
$c(O_{ij}, R_{ij})$	Cost of O_{ij} mapped to resource R_{ij}
$s(O_{ij})$	Start time of job O_{ij}
$e(O_{ij})$	End time of job O_{ij}
d_{ij}	Time limit for completion of O_{ij}
c'_{ij}	cost limit for O_{ij}
$tsum(M_i)$	Running time or Uptime of M_i

- A precedence function

  $p : O\text{x}O \rightarrow \{TRUE, FALSE\}$ for the grid jobs.

- An assignment function $\mu : O \rightarrow P(P(M))$ from grid jobs to resource sets. $P(M)$ is the power set of M. μ_{ij} is the set of all possible combinations of resources from M, which together are able to perform the grid job O_{ij}

- Resource mapping $R : O \rightarrow P(P(M))$, R_{ij} represent mapping of job O_{ij} on a machine M, $R_{ij} \in \mu_{ij}$

- Function $t : O\text{x}P(M) \to \mathbb{R}$, which gives for every grid job O_{ij} the time needed for processing on a resource set $R_{ij} \in \mu_{ij}$
- Cost function $c : O\text{x}P(M) \to \mathbb{R}$, $c(O_{ij}, R_{ij})$ is the cost of job O_{ij} mapped on resource R_{ij}.
- Function $l : M_i \to O_{jk}$ which gives the last grid job executed on resource M_i
- Function $s : O_{ij} \to \mathbb{R}$, $s(O_{ij})$ is the start time of grid job O_{ij}.
- Function $e : O_{ij} \to \mathbb{R}$, $e(O_{ij}) = s(O_{ij}) + t(O_{ij}, R_{ij})$ is the end time of grid job O_{ij} which is mapped on resource R_{ij}.
- Function $tsum : M_i \to \mathbb{R}$ which gives the resource M_i running time or Uptime.

Optimization is done by choosing suitable start times $s(O_{ij}) \in \mathbb{R}$ and resource allocations $R_{ij} \in \mu_{ij}$. A solution is valid, if the following two **restrictions** are met:

1. All grid jobs are planned and resources are allocated exclusively:

   $\forall O_{ij} : \exists s(O_{ij}) \in \mathbb{R}, R_{ij} \in \mu_{ij} : \forall M_j \in R_{ij}$:

   M_j is in $[s(O_{ij}); s(Oij) + t(O_{ij}), R_{ij}]$ exclusively allocated by O_{ij}

2. Precedence relations are adhered to:

   $\forall i, j \neq k : p(O_{ij}, O_{ik}) \Rightarrow s(O_{ik}) \geq s(O_{ij}) + t(O_{ij}, R_{ij})$

Exceeding the time limit and budget cost will affect QoS of grid jobs. A penalty factor is imposed when jobs violates following **constraints**.

1. All grid jobs O_{ij} have time limit d_{ij} which must be adhered to:

   $\forall O_{ij} : d_{ij} \geq s(O_{ij}) + t(O_{ij}, R_{ij})$:

2. All grid jobs O_{ij} have a cost limit c'_{ij} which must be adhered to:

   $\forall O_{ij} : c'_{ij} \geq c(O_{ij}, R_{ij})$

This work focuses on achieving near-optimal scheduling strategy on following objective functions:

1. Minimizing makespan, $e(O_{ij})$ is the end time of grid job O_{ij}

$$f_1 = makespan = max\{e(l(M_1)), e(l(M_2)), \ldots, e(l(M_m))\}$$

Makespan is the time at which all the resources becomes free.

2. Maximizing utilization of resources i.e. minimizing f_2

$$f_2 = non - utilization = \frac{1}{m}\sum_{j=1}^{m}\{e(l(M_j)) - tsum(M_j)\}$$

f_2 is the average time period during which the the resources are idle.

3. Minimizing time limit penalty (minimizing number of jobs completing after due date)

$$f_3 = \frac{1}{j * n}\sum_{\forall i,j} \varphi_1(e(O_{ij}) - d_{ij})$$

where $\varphi_1(x)$ is a non-negative continuous exponential non-decreasing function, if $x > 0$ else 0.

The grid jobs failed to complete within time limit contribute to the penalty function f_3. Minimizing time limit penalty is our aim.

4. Minimizing cost penalty

$$f_4 = \frac{1}{j * n}\sum_{\forall i,j} \varphi_2\{c(O_{ij}, R_{ij}) - c'_{ij}\}$$

where $\varphi_2(x)$ is a non-negative continuous linear non-decreasing function, if $x > 0$ else 0.

The grid jobs failed to meet the cost limit constraint contribute to the penalty function f_4. Minimizing cost limit penalty is our aim.

5. Minimizing Overall Energy consumption

   $f_5 = \sum_{i=1}^{m} tsum(M_i) * W_i$

f_5 gives energy consumption of all the resources.

3.4 MOJS Module

On submission of jobs and grid resource infromation to Multi-Objective Job Scheduler (MOJS) module, it outputs a near optimal scheduling strategy. Some of the important building blocks of scheduler are discussed below.

3.4.1 Multi-objective optimization

Generalized multi-objective optimization problem can be described as:
Minimize $y = f(x) = (f_1(x), f_2(x), \ldots, f_k(x))$
where $x \in \mathbb{V}, y \in \mathbb{R}^k$
where, x is decision vector in search space $\mathbb{V}$, y is the objective vector with $k > 1$ objectives.

3.4.2 Chromosome model

A scheduling strategy or mapping of jobs on resources satisfying the constraints is represented by chromosome. A chromosome stores parameters as follows

- Resource id corresponding to each job
- Start time of every job
- End time of every job

- Predecessor job ID of each job
- Five objective function values
- Rank of chromosome, Rank is defined in section 3.4.3
- Crowding distance, defined in section 3.4.4

Start time for execution of jobs is calculated according to heuristic rules (i) Schedule grid job as early as its precedent job is completed (ii) Schedule grid jobs according to shortest due date.

3.4.3 Non-Dominated Sorting

A chromosome a is said to be dominated by chromosome b iff $\forall i \in \{1, 2, \ldots, k\}$: $f_i(a) \leq f_i(b)$ and $\exists i \in \{1, 2, \ldots, k\}$: $f_i(a) < f_i(b)$. A chromosome a is said to be Non-dominated if there does not exist any chromosome $b \in \mathbb{V}$ search space that dominates a. A set of such non-dominated chromosome in objective space is called pareto optimal front. After removing the pareto optimal front, a second pareto optimal front can be obtained. We assign a rank to each of the chromosome according to their occurrence in the pareto front. Then the algorithm sorts the population according to their rank and crowding distance (discussed in section 3.4.4) for selecting population for next generation. After a certain number of generations any chromosome from the first pareto front satisfying the soft constraints can be chosen as the near optimal solution, or a weighted sum of the objectives can be used for finding suitable solution.

3.4.4 Diversity preservation

It is desired that the evolutionary algorithm maintains a good spread of solutions in the population, so that sustainable diversity in the population remains and solutions are not restricted to local optimization.

Crowding distance

Crowding distance ($dist_x$) of a particular chromosome x in population measures the density of chromosomes surrounding it.
After non-dominated sorting is completed, each chromosome's crowding distance is calculated as the sum of normalized distance between its adjacent neighbors corresponding to each objective. Crowding distance for first and last individual is infinite.

$dist_x = \sum_{j=1}^{k} \frac{f_j(x_{left})-f_j(x_{right})}{f_j^{max}-f_j^{min}}$ where f_j is jth objective function, and number of objectives is k.

Crowded comparison operator

Each chromosome in the population will have two attributes

1. non-domination rank r_x
2. crowding distance $dist_x$

A partial order $\prec$ between chromosomes are defined as: $a \prec b$ if $r_a \prec r_b$ or $(r_a = r_b)$ and $(dist_a \succ dist_b)$

This means that we prefer a chromosome from less crowded region in search space in same front.

3.4.5 NSGA II

Non-dominated Sorting Genetic Algorithm II [12] is used as a basic framework for our Job scheduler module. In NSGA II, initially a random parent population P_0 is created. Using the above relation partial order population is sorted. For the first generation binary tournament selection, recombination, and mutation operators are used to create an offspring population Q_0 of same size as P_0 say N.

Now we describe the tth generation. A combined population $R_t = P_t \cup Q_t$ is formed of size $2N$. Then R_t is sorted according to non-domination. Now best non-dominated set i.e. first pareto front F_1 is chosen for new population. If size of F_1 is less than N then solutions from F_2 are chosen next, followed by F_3 and so on. Now a new population P_{t+1} of size N is chosen after crowding distance sorting. This population is now used for selection, crossover, mutation to generate new offspring population Q_{t+1} of size N , and R_{t+1} is formed by union of P_{t+1} and Q_{t+1}. A schematic explanation of procedure is given in Figure 3.2.

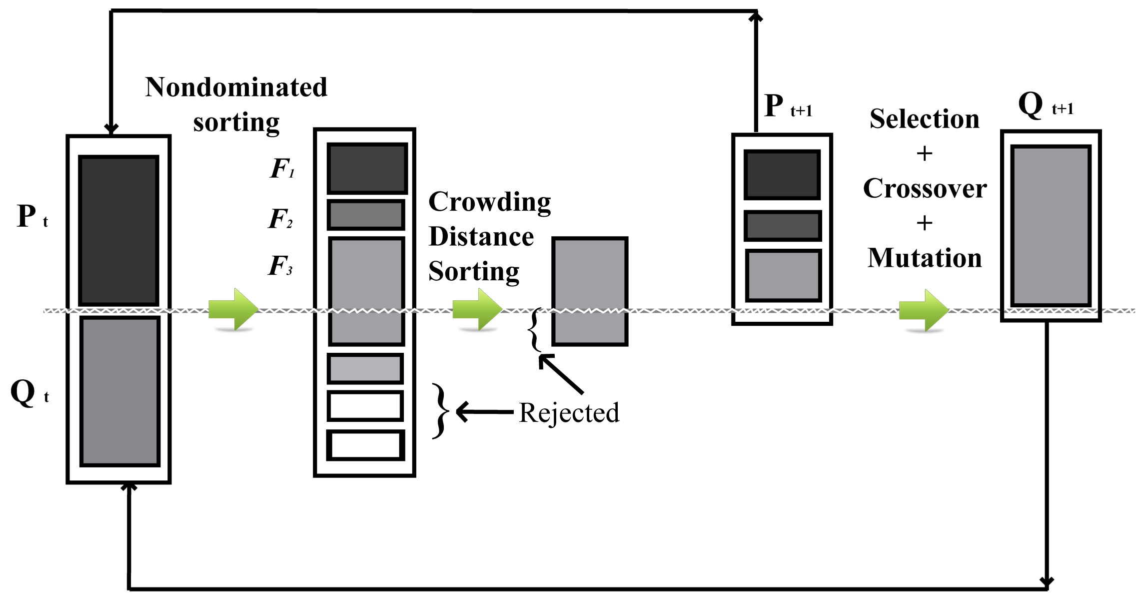


Figure 3.2: NSGA II procedure [12]

3.4.6 Crossover, Mutation and Elitism

Crossover

The crossover operators are the most important part of any evolutionary-like algorithm. In each generation a mating pool of chromosomes is created through a tournament of selection among chromosomes. Two chromosomes are selected from mating pool interchanging their genes to obtain new individuals. The aim is to obtain new individual/chromosome with better fitness function and that will help in exploring new regions in search space not explored yet. P_c is the probability with which crossover operator is applied. Crossover operators depends on the chromosome representation.

One point crossover: Given two parent chromosomes, this operator first randomly chooses a position between 1 and NUM_JOBS. The point act as cutting point. Then the two first parts of the parents are interchanged yielding two new descendants. Schematic representation is given in Figure 3.3.

k-point crossover: This operator is a generalization of one-point crossover.

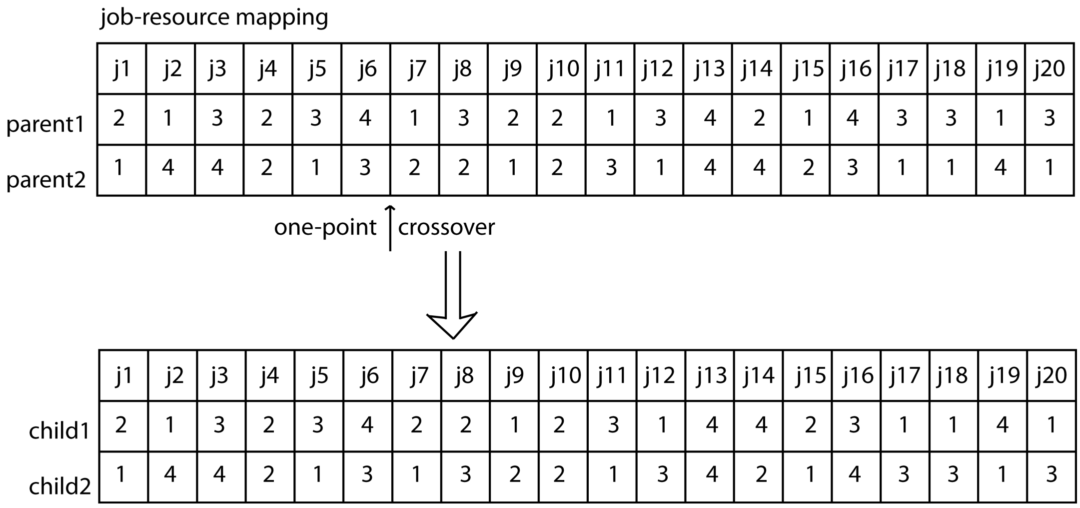


Figure 3.3: One point crossover

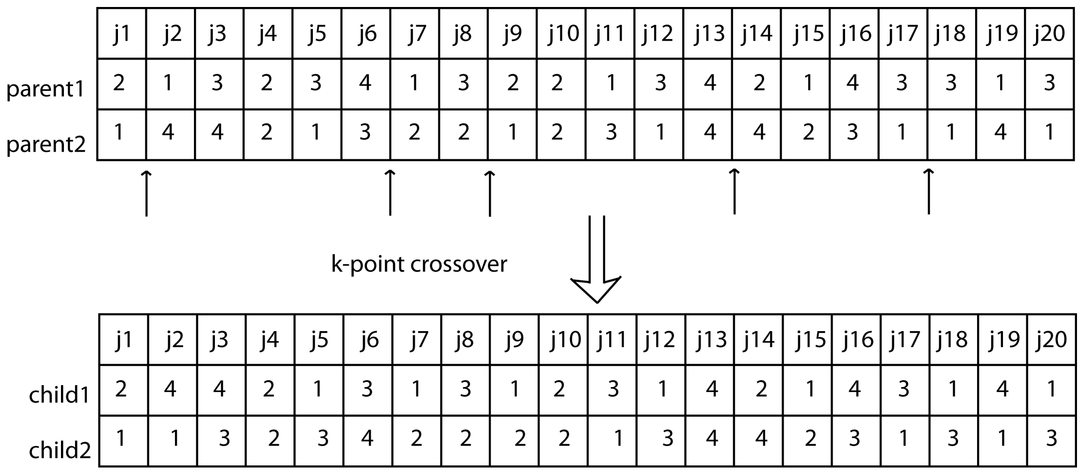


Figure 3.4: k-point crossover

Two or more cutting points i.e. $k \geq 2$ are randomly chosen and segments are interchanged alternately yielding two new descendants. However it should be noticed that large value of k tends to explore more thoroughly the solution space but it is likely that it will destroy parents structure. An example is given in Figure 3.4.

Mask Crossover: A mask array of 0/1's is created randomly of size NUM_JOBS i.e. $mask = m_1, m_2, m_3, \ldots, m_{NUM\_JOBS}$ where $m_i = 0/1$. Figure 3.5 explains this operator.

$$\forall i, chromosome_{new_1}[i] = \begin{cases} chromosome_{parent_1}[i] & \text{if } m_i = 0 \\ chromosome_{parent_2}[i] & \text{otherwise} \end{cases}$$

$$\forall i, chromosome_{new_2}[i] = \begin{cases} chromosome_{parent_1}[i] & \text{if } m_i = 1 \\ chromosome_{parent_2}[i] & \text{otherwise} \end{cases}$$

Fitness based Crossover: In this operator fitness or any other external func-

	j1	j2	j3	j4	j5	j6	j7	j8	j9	j10	j11	j12	j13	j14	j15	j16	j17	j18	j19	j20
parent1	2	1	3	2	3	4	1	3	2	2	1	3	4	2	1	4	3	3	1	3
parent2	1	4	4	2	1	3	2	2	1	2	3	1	4	4	2	3	1	1	4	1
mask	1	0	0	0	1	1	1	1	1	0	1	0	1	0	0	1	1	0	0	1

uniform crossover

	j1	j2	j3	j4	j5	j6	j7	j8	j9	j10	j11	j12	j13	j14	j15	j16	j17	j18	j19	j20
child1	1	1	3	2	1	3	2	2	1	2	3	3	4	2	1	3	1	3	1	1
child2	2	4	4	2	3	4	1	3	2	2	1	1	4	4	2	4	3	1	4	3

Figure 3.5: Mask crossover

tion can be used. Our approach yield two descendants. The crossover is computed as follows. Working methodolgy can be inferred from Figure 3.6.

$$\forall i, chromosome_{new_1}[i] = \begin{cases} chromosome_{parent_1}[i] & \text{with probability } p = \frac{g_1[i]}{g_1[i]+g_2[i]} \\ chromosome_{parent_2}[i] & \text{with probability } 1 - p \end{cases}$$

$$\forall i, chromosome_{new_2}[i] = \begin{cases} chromosome_{parent_1}[i] & \text{with probability } p = \frac{h_1[i]}{h_1[i]+h_2[i]} \\ chromosome_{parent_2}[i] & \text{with probability } 1 - p \end{cases}$$

	j1	j2	j3	j4	j5	j6	j7	j8	j9	j10	j11	j12	j13	j14	j15	j16	j17	j18	j19	j20
parent1	2	1	3	2	3	4	1	3	2	2	1	3	4	2	1	4	3	3	1	3
parent2	1	4	4	2	1	3	2	2	1	2	3	1	4	4	2	3	1	1	4	1

normalized	r1	r2	r3	r4
energy parameter	0.9	0.85	1.0	0.7
processing parameter	0.85	0.6	0.7	1.0

probability of inherence of gene for child1 from

parent1	0.485	0.562	0.588	0.5	0.526	0.411	0.514	0.540	0.485	0.5	0.473	0.526	0.5	0.548	0.514	0.411	0.526	0.526	0.562	0.526

fitness over energy parameter

probability of inherence of gene for child2 from

parent2	0.413	0.459	0.411	0.5	0.451	0.588	0.586	0.538	0.413	0.5	0.548	0.451	0.5	0.375	0.586	0.588	0.451	0.451	0.459	0.451

fitness over processing capability parameter

Figure 3.6: Fitness based crossover

Each resource in grid has processing capability and energy efficiency parameter. They almost counteract each other and need a tradeoff between them to find optimal schedule.

Here $g_1[i], g_2[i]$ are energy efficiency parameter of $chromosome_{parent_1}[i]$ and $chromosome_{parent_2}[i]$ respectively. Similarly $h_1[i], h_2[i]$ are processing capability parameter of $chromosome_{parent_1}[i]$ and $chromosome_{parent_2}[i]$ respectively.

Mutation

P_m is the probability with which mutation operator is applied. Mutation operators used as follows.

Move: This operator randomly assigns a resource to the job. Care is taken that resource type is same i.e. resource belongs to same set.

Swap: This operator randomly chooses two jobs and swap their assigned resources if they belong to same set.

Rebalancing: This operator takes into account number of jobs assigned to each resource. This operator chooses most overloaded resource and randomly pick a job assigned to it. Then the job is moved to a resource which is less overloaded.

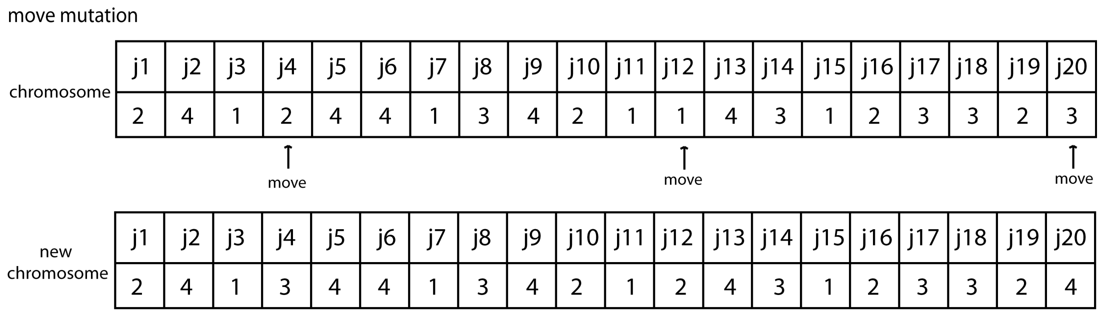


Figure 3.7: Mutation- move

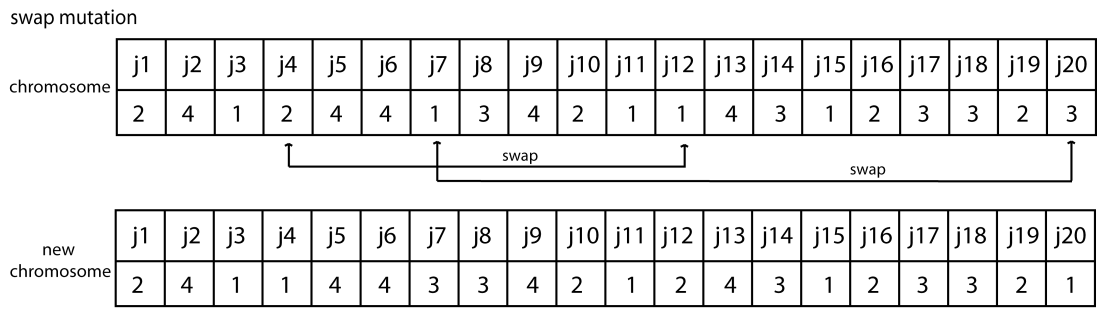


Figure 3.8: Mutation- swap

Elitism

In the process of crossover and mutation it is possible that some good chromosomes might be lost. Elitism is a mechanism to preserve these chromosomes. A small percentage of the fittest population i.e. first pareto front in multi-objective search space is forwarded to be the part of new population for next iteration.

3.5 Dynamic scheduling

Application jobs queued in grid are fed to the MOJS module in batch. The output is the elitist pareto front of chromosomes comprises near optimal schedules. Soft constraints and weighted sum approach is applied on multiple objectives to finalize a chromosome as scheduling strategy. Some jobs are queued on their respective resource while others are again fed to MOJS module. The number of jobs queued depend on the fitness of the chromosome and time available for the scheduler to re-run and find a better schedule. Progress is ensured by setting a minimum number of jobs to be queued on a single run of module.

As this is a real time scheduling problem and resources are dynamic in nature it can participate and leave the system any time, it is of higher importance to make the scheduling dynamic in nature. By dynamic we mean re-allocation of already scheduled jobs which were not completed. So change in the resource pool can trigger running of scheduler which can either reschedule the jobs whose resources have left the grid or can request processing of new jobs on addition of one or more resources or both of them. Jobs whose predecessors is present in the set of rescheduled jobs are also rescheduled.
There is very little scope for this paper to solve the issue where a job suffers starvation and penalty due to failure of resource. To handle this issue accounting of Mean Time to Failure (MTTF) with log mining can help.

3.6 Job Grouping for Fine-grained Jobs

Fine grained jobs are grouped to form a single job. Following are the constraints considered while job grouping.

- Jobs grouped as single job should be of same type i.e. either computational jobs or storage intensive jobs.
- Prevail same job precedence rule after job grouping.

Workflow and precedence of jobs is represented through Directed Acyclic Graph (DAG), where nodes are jobs and directed edge represents precedence.
A directed edge from a to b is drawn, when b awaits for the completion of job a and a is said to be the predecessor of b and b is the successor of a. Nodes having common edge are defined as adjacent nodes. We define a, b to have same job type if their resource type requirement is same.
Before we present our heuristic algorithm for job-grouping, we define few terms as follows:

3.6.1 Entry job

A job without any predecessor but has atleast one successor is called entry job. If there are multiple entry jobs for a DAG component then we add a zero size job/node and new directed edges are drawn from zero size job to entry jobs. Hence we have a single entry job denoted as j_{entry}.

3.6.2 Exit job

A job without any successor but has atleast one predecessor is called exit job. If there are multiple exit jobs for a DAG component then we add a zero size job/node and new directed edges are drawn from exit jobs to zero size job. Hence we have a single exit job denoted as j_{exit}.

3.6.3 Job size

Size of a computational job is measured in Million Instructions(MI) and storage jobs in Megabytes(MB). It is denoted as $job\_size(j)_{computational}$ or $job\_size(j)_{storage}$.

Note:

- A computational job has $job\_size(j)_{storage} = 0$ MB
- A storage job has $job\_size(j)_{computational} = 0$ MI

3.6.4 Critical length

Critical length denoted as $crit(j)$ refers to the longest distance from j_{entry} to j_{exit} passing through the job j. There are two types of jobs viz., computational intensive and storage intensive jobs. Hence we consider $crit(j)_{computational}$, $crit(j)_{storage}$ accordingly for calculation in Algorithm 1 depending on the job type.
The Upward Critical length of job j is the longest distance from j to the exit job j_{exit}. It is denoted as $crit_{up}(j)_{<type>}$ where ${}_{<type>}$ is computational and storage.

Algorithm 1 job grouping

Input: Job pool with DAG representation
Compute $crit_{up}(j)_{<type>}$ for each job j according to the equation 3.1
Compute $crit_{down}(j)_{<type>}$ for each job j according to the equation 3.2
Compute $crit_{<type>}$ for each job j according to the equation 3.3
while Job $a \in$ job pool exists, where a is unprocessed fine-grained job **do**
  $flag \leftarrow 0$
  while a is fine-grained job **and** $flag = 0$ **do**
    for each $b \in adjacent\_node(a)$ **and** same type i.e. computational or storage **do**
      Temporary merge adjacent node b and a to form t
      Calculate new $crit_{up}(t)_{<type>}$, $crit_{down}(t)_{<type>}$ and $crit(t)_{<type>}$
      if new $crit(t)_{<type>} \leq crit(j_{entry})_{<type>}$ **and** $crit(t)_{<type>}$ is minimum till now **then**
        $merge\_node \leftarrow b$
      end if
    end for
    if $merge\_node$ is found **then**
      Permanently merge $merge\_node$ with a to form a'
      Change parent and child relation accordingly
      if a' is not fine-grained job **then**
        $flag \leftarrow 1$
      end if
    else
      $flag \leftarrow 1$
    end if
  end while
end while

Upward critical length is computed with the equation 3.1 starting from $jexit$ and moving upward towards j.

$$crit_{up}(j)_{<type>} = job\_size(j)_{<type>} + max_{j' \in succ(j)}(crit_{up}(j')_{<type>}) \tag{3.1}$$

Similarly, the Downward Critical length of job j is the longest distance from the entry job j_{entry} to j. It is denoted as $crit_{down}(j)_{<type>}$ where $_{<type>}$ is computational and storage. Downward critical length is computed with the equation 3.2 starting from $jentry$ and moving downward towards j.

$$crit_{down}(j)_{<type>} = job\_size(j)_{<type>} + max_{j' \in pred(j)}(crit_{down}(j')_{<type>}) \tag{3.2}$$

$$crit(j)_{<type>} = crit_{up}(j)_{<type>} + crit_{down}(j)_{<type>} \tag{3.3}$$

Note: $crit(j_{entry})_{<type>}$ is the longest distance from j_{entry} to j_{exit} in the DAG. The path with the longest distance from the j_{entry} to j_{exit} is called *critical path.* Any job whose $crit(j)_{<type>}$ value is equal to $crit(j_{entry})_{<type>}$ is on a critical path is considered as a critical job. The heuristic applied in algorithm 1 is to group fine-grained jobs without increasing the critical path length of the DAG.

3.7 Algorithm Description

Algorithm 2 MOJScheduler

Input: Jobs[NUM_JOBS],Resource[$NUM\_RESOURCES$],n,$num\_iteration$

```
Initialization: Generate initial population P_0 of n chromosomes
Fitness Calculation:
for i = 1 → n do
    Evaluate(chromosome[i] from P_i)
end for
for i = 1 → num_iteration do
    Selection: Select a subset of even number of chromosomes from P_i
    P_{i1} = Select(P_i)
    Crossover: With probability P_c crossover every two chromosome from P_{i1}
    P_{i2} = crossover(P_{i1})
    Mutation: With probability P_m mutate chromosome from P_{i2}
    P_{i3} = mutate(P_{i2})
    Fitness Calculation:
    for i = 1 → n do
        Evaluate(chromosome[i] from P_{i3})
    end for
    P_{i4} = P_i + P_{i3}
    Assign non-domination rank to each chromosome, Non-dominating_Sort(P_{i4})
    calculate_crowding_distance(P_{i4})
    Sort based on Crowding distance of each chromosome
    crowding_distance_sorting(P_{i4})
    Replacement: Create population for new generation
    Forward 1st n chromosomes from sorted set P_{i4} to P_{i+1}
end for
return Chromosomes with non-domination rank 1 i.e. First pareto front
```

Algorithm 3 crossover(P_i)

Input: Set of chromosomes P_i with population $2m$,P_c

  Initialize set Q
  for $i = 1 \to m$ **do**
    Randomly choose two chromosome x, y from P_i
    $p = random\_double(0, 1)$, $random\_double(x, y)$ generates a number $[x, y]$
    if $p < p_c$ **then**
      $c = random\_int(0, 2)$, $random\_int(x, y)$ generates an integer $[x, y]$
      if $c = 0$ **then**
        $k \leftarrow random\_int(0, 10)$
        $x_1, y_1 = k\_point\_crossover(x, y)$
        Add x_1, y_1 to Q
      end if
      if $c = 1$ **then**
        $x_1, y_1 \leftarrow uniform\_crossover(x, y)$
        Add x_1, y_1 to Q
      end if
      if $c = 2$ **then**
        $x_1, y_1 \leftarrow fitness\_based\_crossover(x, y)$
        Add x_1, y_1 to Q
      end if
    end if
  end for
  return Set Q

Algorithm 4 mutation(P_i)

Input: Set of chromosomes P_i, P_m

```
for i = 1 → size(P_i) do
  Select chromosome[i]
  p = random_double(0, 1), random_double(x, y) generates a number [x, y]
  if p < p_m then
    c = random_int(0, 2), random_int(x, y) generates an integer [x, y]
    if c = 0 then
      count = random_int(1, 10), change at most 10 genes
      for i = 1 → count do
        pos = random_int(0, NUM_JOBS)
        Assign a new resource to gene pos from same resource type
        move(chromosome[i],pos)
      end for
    end if
    if c = 1 then
      count = random_int(1, 10), change at most 10 genes
      for i = 1 → count do
        pos_1 = random_int(0, NUM_JOBS)
        pos_2 = random_int(0, NUM_JOBS)
        Assign a new resource to gene pos from same resource type
        swap(chromosome[i],pos_1,pos_2)
      end for
    end if
    if c = 2 then
      count = random_int(1, 10), change at most 10 genes
      for i = 1 → count do
        pos = random_int(0, NUM_JOBS)
        Assign a new resource to gene pos from same resource type
        rebalancing(chromosome[i],pos)
      end for
    end if
  end if
end for
return Set P_i
```

Algorithm 5 calculate_crowding_distance(P_i)

Input: Set of chromosomes P_i

$l = size(P_i)$
for $i = 1 \to l$ **do**
  $dist_{chromosome[i]} = 0$
end for
for $m = 1 \to num\_obj$, Here number of objective i.e. num_obj functions is 5 **do**
  sort(P_i,m)
  $dist_{chromosome[1]} \leftarrow \infty$
  $dist_{chromosome[l]} \leftarrow \infty$, ensuring boundary chromosomes are always there
  for $i = 2 \to l - 1$ **do**
    $dist_{chromosome[i]} = dist_{chromosome[i]} + \frac{f_{chromosome[i+1]_m} - f_{chromosome[i-1]_m}}{f_m^{max} - f_m^{min}}$
    where $f_{chromosome[i]_m}$ is mth objective function of $chromosome[i]$
    f_m^{max} is max value of mth objective function &
    f_m^{min} is min value of mth objective function
  end for
end for
return Set P_i

Chapter 4

Implementation and Results

We have implemented our proposed scheduler and simulated the grid environment with standard worloads. The dispatcher uses Message Passing Interface(MPI) communication environment to interact with the resources and submit jobs. In this chapter implementation methods and experimentation details of scheduler and its performance based on various parameters have been discussed.

4.1 Implementation Details

We have implemented our work in C++ programming language. The job scheduler module schedule jobs. The resource manager simulates the dynamic behaviour of resources in grid. An initial configuration of the online resources is considered before starting the job scheduling process. The dispatcher send jobs to corresponding resources.

Implemented system with job scheduler module has following features.

- Preprocessing of fine-grained jobs for reducing computing complexity of job scheduler.
- Flexibility of choosing best scheduling strategy from first pareto front. First pareto front represents non-dominating sets of strategies based on objective parameters.

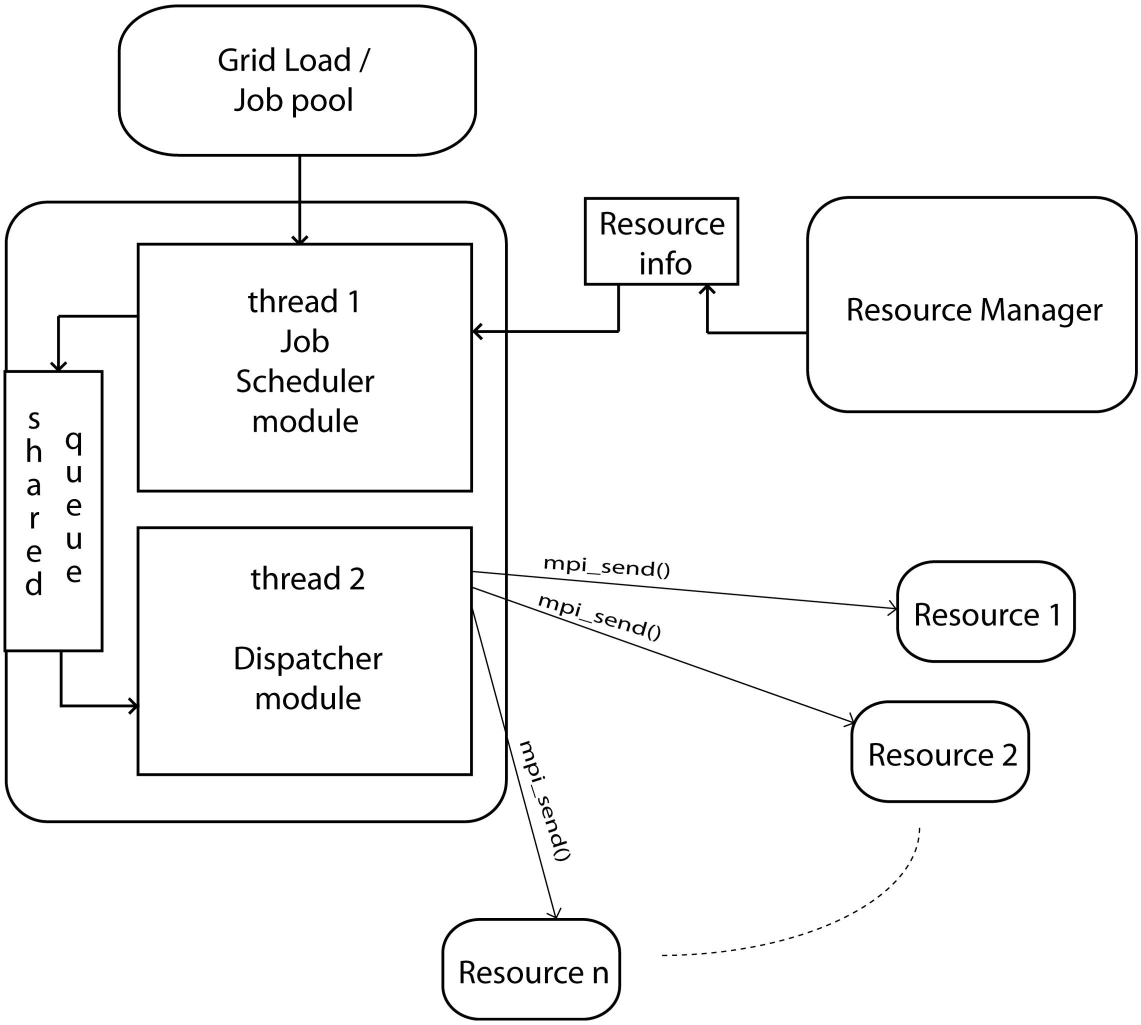


Figure 4.1: Implemented System model

- Normalized weighted sum approach, where weights can be changed dynamically assigned based on the change in grid behaviour.
- Configuring resources on the fly. Adding, modifying and deleting resources via resource manager.
- Real time job scheduler.

4.2 System model

Here we discuss detailed architecture of the implemented system. We have used posix thread to share the scheduling or mapping queues with the dispatcher. The Multi-objective Job Scheduler module run on one thread and dispatcher on another.

The scheduler act as a producer and the dispatcher as a consumer. To simulate the grid environment the dispatcher sends job details through MPI to its mapped resource. The resources waiting for the messages on receiving job, run dummy jobs with the parameters passed on to it. Figure 4.1 is the schematic representation of the implemented system.
Dispatcher and scheduler maintains separate queues for separate resources. When a resource goes down, jobs of that queue is rescheduled on available resources.

4.2.1 Job queue

It have been considered that a job requires a single core of processor for execution. Table 4.1 represents a segment of job queue. Each grid job has following properties:

- JOB_ID is an unique identifier for a job.
- Grid jobs are either CPU intensive or I/O intensive represented as JOB_TYPE 0/1 respectively.
- $PRED\_ID$ is the predecessor job on which the job is dependent. -1 represent no dependencies on other job.
- JOB_SIZE of CPU intensive jobs are either represented in MI (Million Instruction).
- JOB_SIZE of I/O intensive jobs are either represented in MB (Mega Bytes).
- $TIME\_LIMIT$ is a constraint for job completion, exceeding time limit imposes penalty. Unit of $TIME\_LIMIT$ is seconds.
- JOB_COST is the expected cost to be incurred by the user based on the QoS agreement. Unit of JOB_COST is currency e.g. USD($).

4.2.2 Resource model

Resource manager configures each resource with the following properties. Table 4.2 shows configuration of some of the resources in grid.

Table 4.1: User job queue

JOB_ID	JOB_SIZE in MI/MB	$TIME\_LIMIT$ in seconds	JOB_COST in \$	$PRED\_ID$	JOB_TYPE
⋮	⋮	⋮	⋮	⋮	⋮
42	24,000 MI	63.0	5.41	29	0
43	130,000 MI	107.0	4.86	-1	0
44	10,500 MI	106.0	5.99	24	0
47	530.0 MB	150.0	5.04	29	1
48	240,200 MI	133.0	5.40	31	0
⋮	⋮	⋮	⋮	⋮	⋮

- $RESOURCE\_ID$ is an unique identifier for a resource.
- Resources are either computing resource or storage resource represented as RES_TYPE 0/1 respectively.
- Computational resource processing capability is measured in MIPS (Million Instruction per second) or IPS(Instruction Per second) per core, and for storage resources it is measured in MB/s. We denote it as RES_CAP [37].
- Another resource parameter is power dissipation/consumption figure in watts. RES_ENERGY is also represented in a normalized form [38].

> Resource power dissipation figure is measured in Watts. Resource with maximum power dissipation figure is found and scaled to 1.0. Similarly other resources power dissipation figures are scaled with maximum power dissipation figure. For example Intel Core i7 920 (Quad core) consumes 130 Watts and Intel Core 2 X6800 (Dual core) consumes 75 Watts, 130 Watts is normalized to 1.0 and 75 Watts to 0.577 [38].

- RES_COST is the cost of the resource per second.

Resources manager module updates available resources information in a file which is being read by Job scheduler module before each run.

Table 4.2: Resource configuration

RESOURCE_ID	*RES_COST* in $	*RES_TYPE*	*RES_ENERGY* *normalized*	*RES_CAP* in MIPS/MBPS
⋮	⋮	⋮	⋮	⋮
4	0.13	0	0.943	9,726 MIPS
5	0.14	0	1.000	29,621 MIPS
6	0.13	0	0.577	13,539 MIPS
7	0.11	1	0.894	30.0 MBPS
⋮	⋮	⋮	⋮	⋮

4.2.3 Output of scheduler

The scheduler yields mapping of jobs and resources with start time and expected execution time of each job. Each resource has its own queue. A queue of jobs mapped to resource id 1 is shown in Table 4.3

Table 4.3: Mapping queue for RESOURCE_ID 1

JOB_ID	*RES_ID*	*START_TIME* in seconds	*EXEC_TIME* in seconds
⋮	⋮	⋮	⋮
95255	1	952.42	138.30
95259	1	1090.73	78.58
95205	1	1169.31	37.71
95306	1	1207.03	62.86
95301	1	1269.90	59.72
95337	1	1329.62	194.88
⋮	⋮	⋮	⋮

4.2.4 Randomize function

In any stochastic algorithm randomize function plays an important role. A very fast random number generator Mersenne Twister of period $2^{19937} - 1$ is used in different parts of the code and has a better equidistibution property. It generates integer in the range 0 to $2^{32} - 1$ and real number range $[0, 1)$ with a precision of 2^{32} [34].

4.3 Data Sets

Standard grid workload from Grid Workload Archive have been used in this experiments [18]. The traces and logs of different grid environments are given in standard gwf format. Gridloads are processed to add a few more parameters like cost of jobs, jobs time limit for completion, predecessor dependencies among jobs and type of jobs.

SHARCNET & DAS-2 are the two traces that have been processed. Traces shows that execution time of jobs ranges from 1 to 20000 time units in DAS-2, and 1 to 100000 time units in SHARCNET. This shows job characteristic varies widely making scheduler task difficult.

For analyzing the performance based on various parameters following workloads have been created given in Table 4.4.

Table 4.4: Gridlet configuration

Workload_id	Trace	Precedence constraint	Resource constraint
1	DAS-2	✗	✗
2	SHARCNET	✗	✗
3	DAS-2	✗	✓
4	SHARCNET	✗	✓
5	DAS-2	✓	✗
6	SHARCNET	✓	✗
7	DAS-2	✓	✓
8	SHARCNET	✓	✓

Workloads are created on the basis of imposing constraints on traces. Job precedence rule is referred to as precedence constraint and constraint of executing jobs on particular type of resource is referred to as resource constraint. Predecessor jobs have been created with the statistics given in table 4.5

Table 4.5: Precedence Constraints

Percentage of Jobs	50%
Range	[JOB_ID -100 , JOB_ID -1]
Mean	[JOB_ID -50]
Variance	20

4.4 Results

In order to evaluate the performance of our scheduler we have performed set of experiments on the workloads mentioned in section 4.3. The scheduler can schedule 200 jobs in 21 seconds. For more optimized results chromosome population and iteration in our algorithm can be increased.

4.4.1 Experiment on independent jobs

Experiment results given in Figure 4.2, 4.3, 4.4, 4.5 on workload 1 and 2 shows minimization of makespan and proper utilization of resources on independent jobs. Result shows that irrespective of the large variation of granularity in grid jobs we have achieved 99%+ utilization performance in almost every resource. Result shows the scalability of our scheduler, we have tested the scheduler with 5000, 10000, 15000, 20000, 25000 jobs; and on 10, 15, 20, 25 resources. This shows that scheduler can process large amount of gridlets and resources without compensating on the Makespan and utilization of resources. The scheduler have yield near optimal mapping strategy optimizing on the time limit limit penalty and cost penalty referred in section 3.3.

4.4.2 Trade off between energy consumption and performance

Now energy parameter and performance parameter is considered while scheduling. It is worthy to note that if job is scheduled on high performance resource less time will be required for job completion and time limit constraint can be satisfied. Again, a job will try to be mapped on a energy efficient resource minimizing overall power

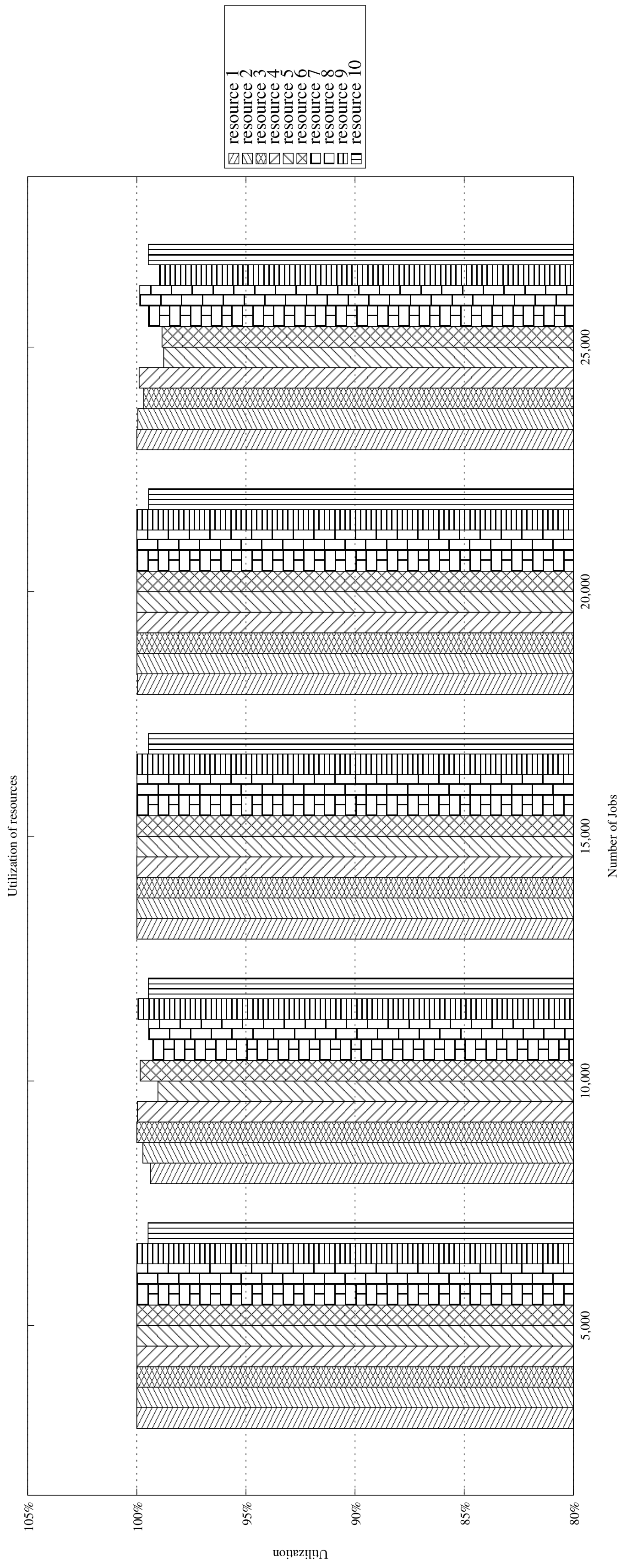


Figure 4.2: Evaluation of makespan and utilization on 10 resources on workload 2

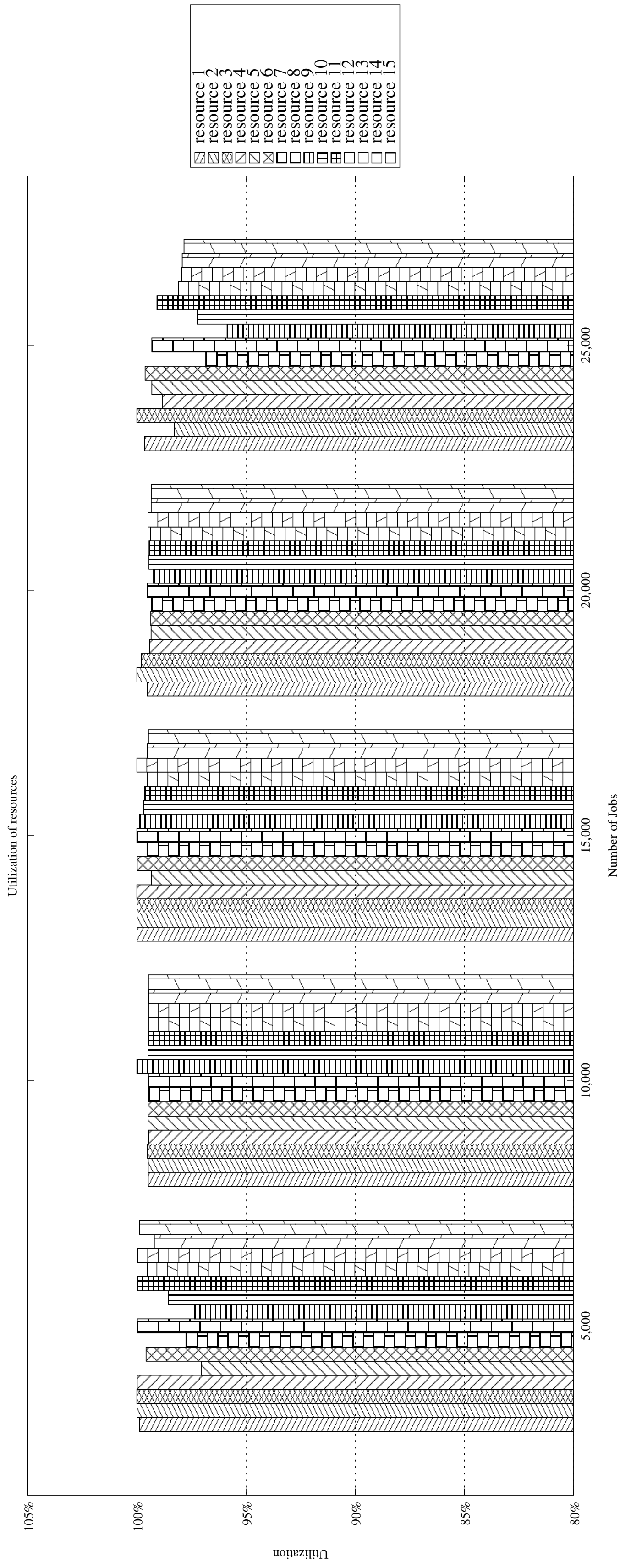


Figure 4.3: Evaluation of makespan and utilization on 15 resources on workload 1

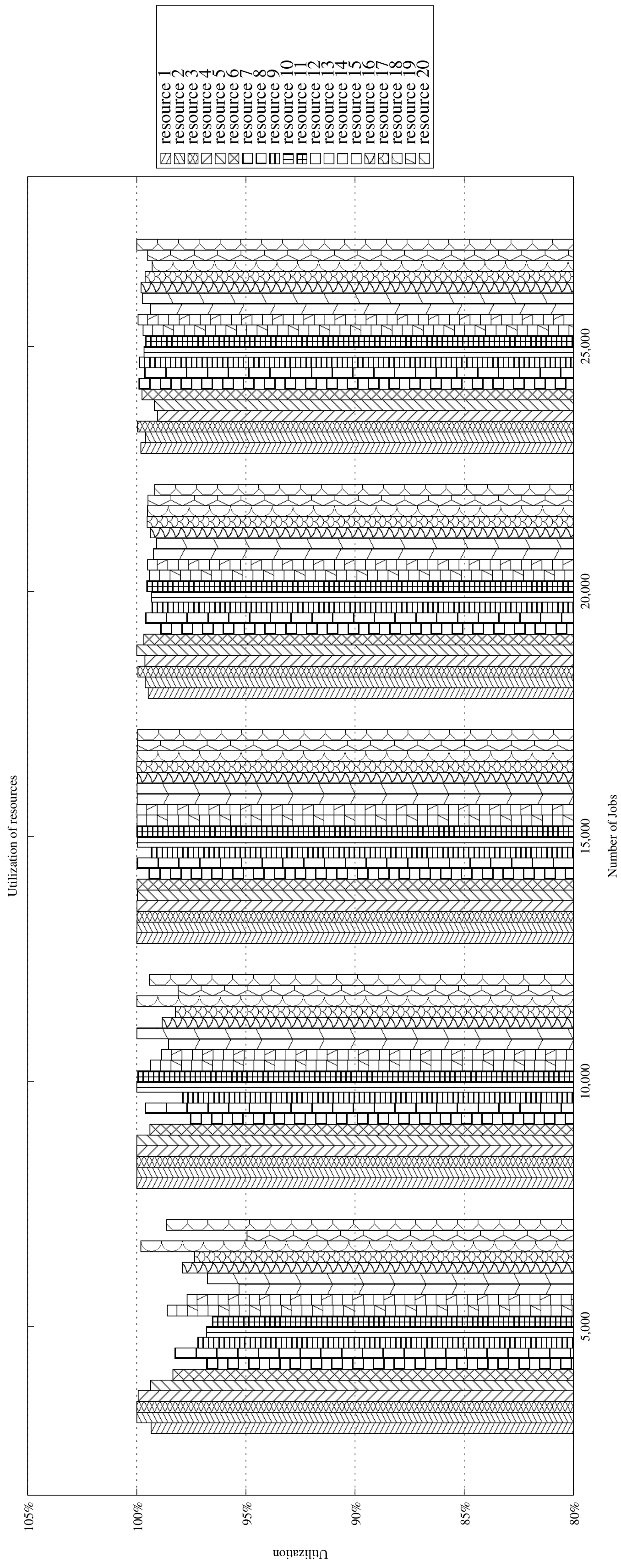


Figure 4.4: Evaluation of makespan and utilization on 20 resources on workload 1

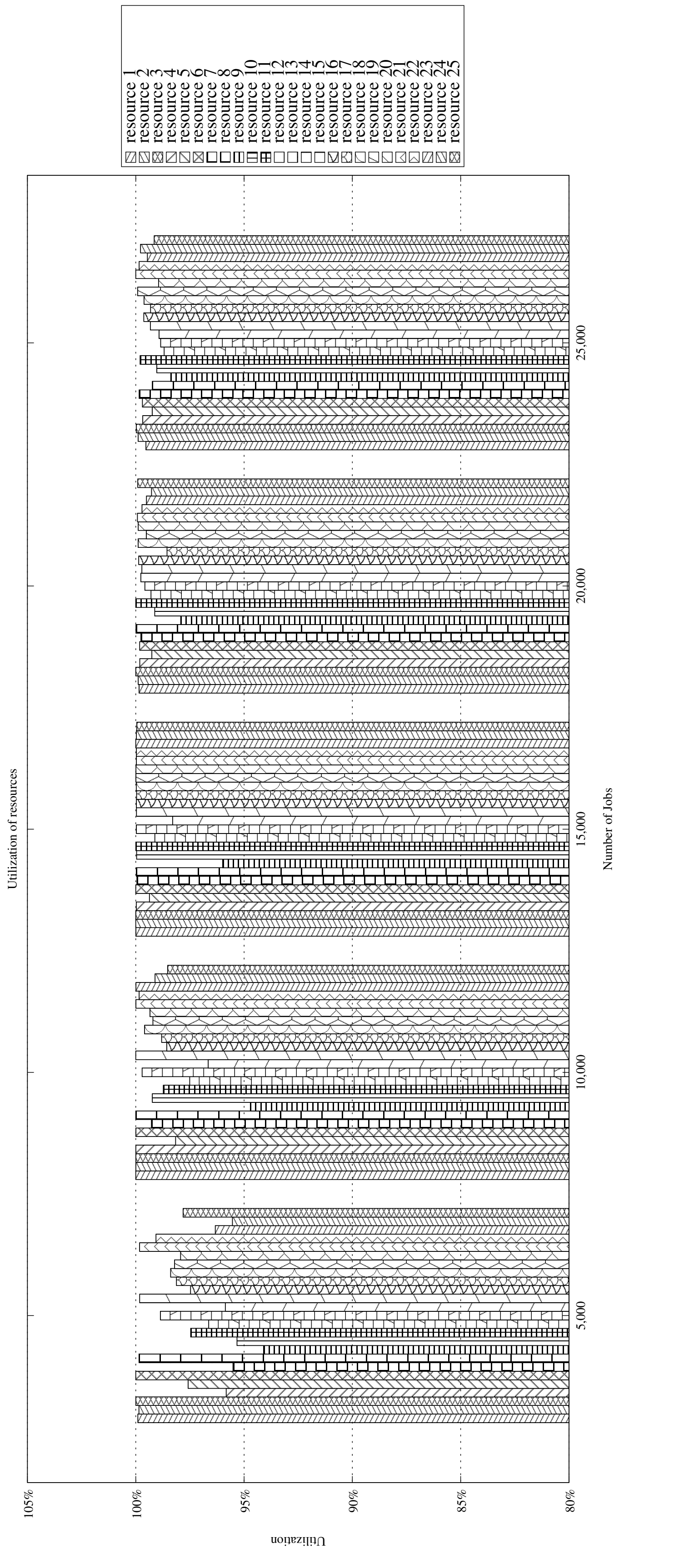
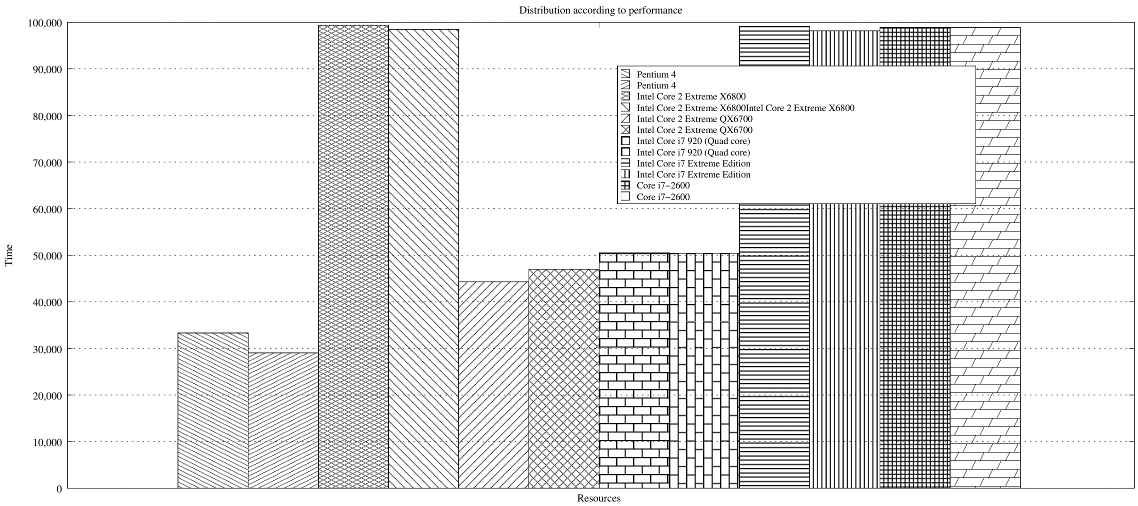
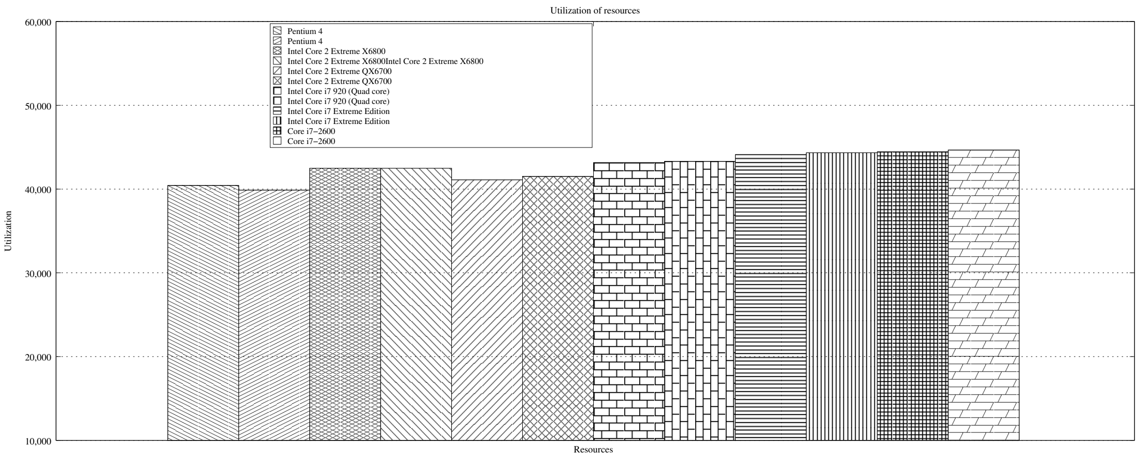


Figure 4.5: Evaluation of makespan and utilization on 25 resources on workload 2



(a) Workload 2 (SHARCNET)



(b) Workload 1 (DAS-2)

Figure 4.6: Evaluation of Ultilization on workload 1 and 2

consumption.

Usually resources with high performing capability are less energy efficient. Jobs having large time limit can afford to be scheduled on low performance resource with low power consumption figures without being penalized for exceeding time limit. However high priority jobs needs high performance resource to process jobs within time limit.

The results given in Figure 4.6(a) have been obtained by assigning equal weights on performance and energy efficiency objective on pareto front 4.7. Resource configuration for this experiment is given in Table 4.6. Experiment result for workload 2 is shown in Figure 4.6(a). Pentium 4 being poor in performance and energy dissipation factor as compared to other resources, have less uptime or running time. Now

Table 4.6: Resource configuration for experiment on workload 1 and 2

Machine	Frequency	Watts	MIPS/core	Resource_id
Pentium 4 Extreme Edition	3.2 GHz	92.1	9,726	1,2
Intel Core 2 X6800 (Dual core)	2.93 GHz	75	13,539	3,4
Intel Core 2 QX6700 (Quad core)	2.66 GHz	95	12,290	5,6
Intel Core i7 920 (Quad core)	2.667 GHz	130	20,575	7,8
Intel Core i7 3960X (Hex core)	3.3 GHz	130	29,621	9,10
Core i7-2600	3.4 GHz	95	32,075	11, 12

comparing resources Core 2 X6800 with Core 2 QX6700, they have almost same MIPS specification but Core 2 X6800 consumes less power. Figure 4.6(a) shows that scheduler have allocated more jobs in Core 2 X6800 which is reasonable. Same logic can be applied for resources Core i7 920 and Core i73960X. They have same energy dissipation factor but Core i7 3960X performance is better. As a consequence scheduler have scheduled more jobs on Core i7 3960X. Best resource of the lot is Core i7-2600. The scheduler have uniformly distributed jobs among Core 2 X6800, Core i7 3960X and Core i7-2600 to have a minimum makespan.

Since workload 2 has large variation in the granularity of jobs the graph shows a worst case analysis in their utilization. In the best case scheduler will try to schedule jobs such that running time on each resource is same 4.6(b).

Figure 4.7 shows how our scheduler gives a better grip to the administrator to trade off between user objectives and grid administrator objectives. Each point on the space represents a scheduling strategy. In a 3D co-ordinate system we represents 3 objectives which are needed to be minimized namely (i) makespan (ii) Energy efficiency parameter, (iii) time targidity. Any point in the first pareto front can be chosen for scheduling strategy. This gives grid administrator wide range of choices and cope up with dynamic behaviour of grid.

4.4.3 Experiment: Introducing job type constraint

Now we introduce the job type constraint in our experimental analysis. Workload 3 and 4 referred in Table 4.3 have been used in this experiment. There are two type of jobs in the worload. On each workload we varied job percentage as 30%-70%,

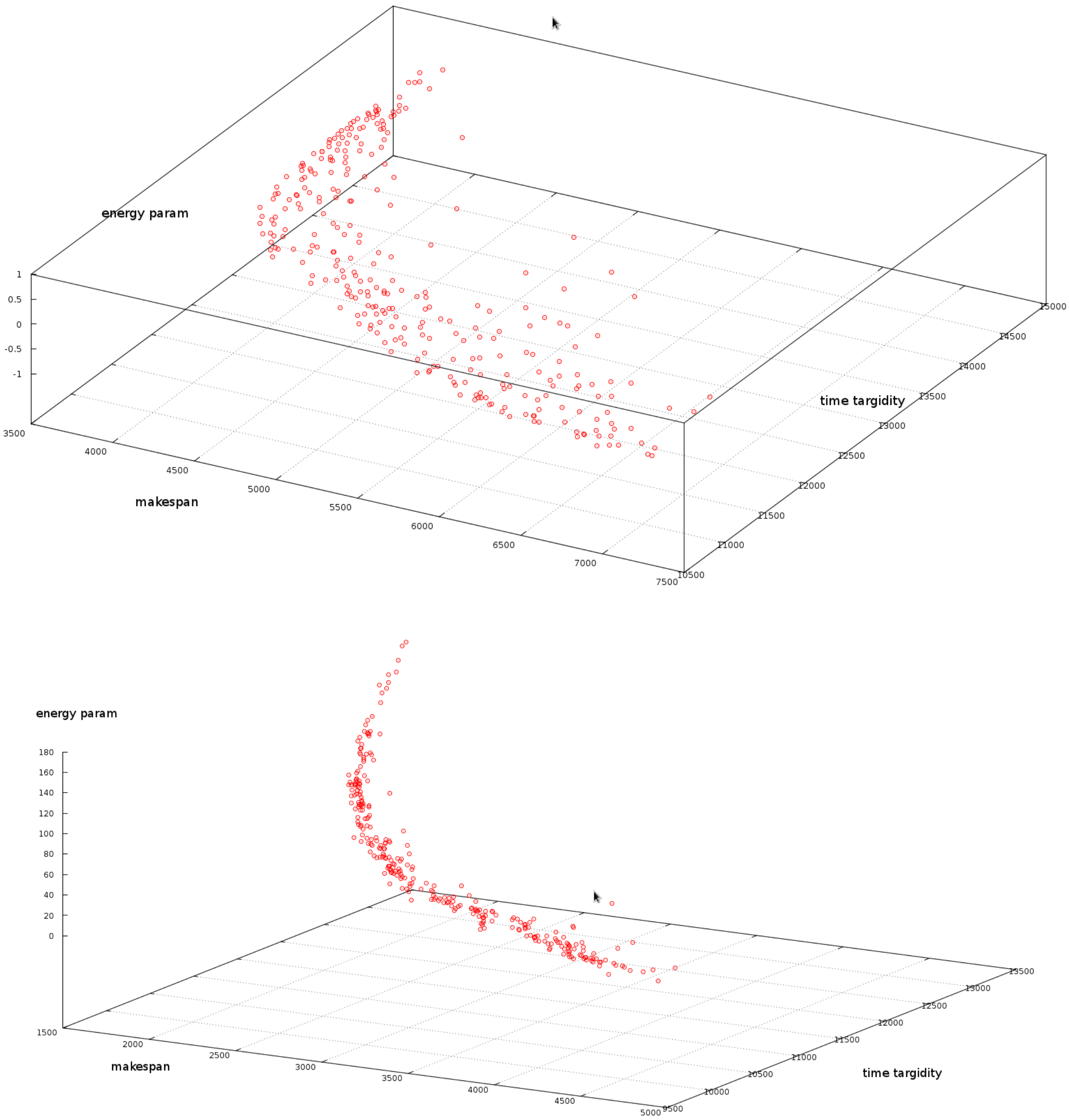


Figure 4.7: pareto front for makespan, time targidity and energy efficiency

50%-50%, 70%-30% to show the adaptiveness of our scheduler. A batch of 7000 jobs were taken which makes makespan of range 10^7 to show the analysis in graph. Figure 4.8 shows uniform utilization among same type of resources inspite of the variance of job type percentage. One thing is further noticeable that analysis of section 4.4.2 still holds. Intel core i7 920 and Core i7-2600 performed equally well whereas Pentium 4 have disappointed again.

For choosing a scheduling strategy from first pareto front weighted sum technique on normalized objectives have been used. For the result shown in Figure 4.8 and

4.9 equal weight was assigned on each objective.

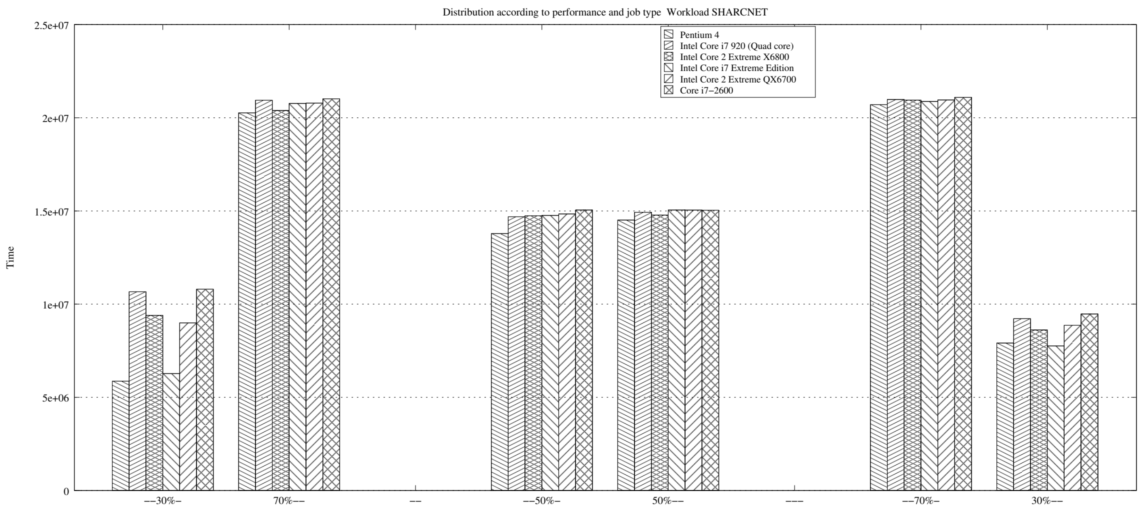


Figure 4.8: Performance under Job type constraint, SHARCNET Workload

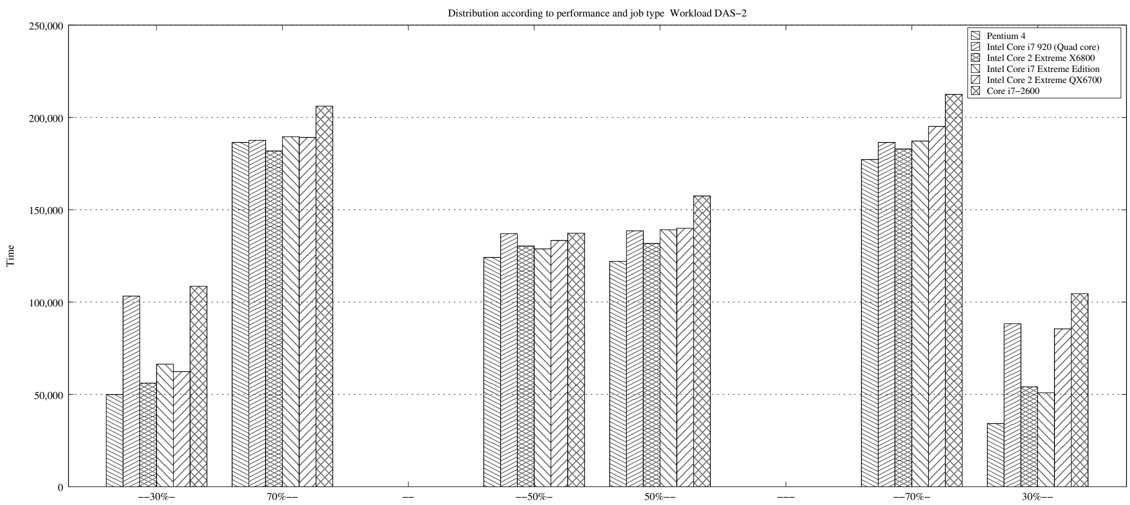


Figure 4.9: Performance under Job type constraint, DAS-2 Workload

4.4.4 Experiment: Introducing pricing model and precedence constraint

In this phase of experiment pricing parameter is incorporated in resource model. Experimented result shows how pricing model can change the utilization of resources. Workload 5 & 6 have been used for this experiment having 50% of job with predecessor dependencies referred in Table 4.3.

Resources which are both low in performance and poor in energy efficiency is cheap in price, whereas high performance resource with less energy dissipation figure is preferred. Jobs having low job cost or high time limit can afford to run on these cheap resources whereas high priority jobs demanding high performance run on costly resources. Trade off among performance, time of execution and cost have allowed jobs to be scheduled on various resources uniformly. In table 4.7 & 4.8 it is observed that resources have adhered to the makespan and all have 98%+ execution time. Utilization percentage shows actual uptime or running time of resources. This reveals that all resources have been utilized properly. Even resources like Pentium 4 have 95% utilization on average.

> A question might arise in reader's mind "Why resource utilization is not 100 percent?". Jobs are having some precedence constraints; and a job scheduled on its compatible resource might take a little longer time to complete, forcing dependent jobs to wait on other idle resource.

In our experiment we have given equal weight to cost pricing, utilization of resources, time limit constraint and makespan. The grid administrator can configure the weight function to obtain required schedule strategy from first pareto front in search space like one given in figure 4.7.

Table 4.7: Resource Utilization after introduction of Job constraint and pricing model Workload 6 (SHARCNET)

ID	Resource	Pricing model	Execution time	Makespan %age	Actual utilized time	Utilization %age
1	Pentium 4	0.05	12048592.25	98.01	11813044.19	98.04
2	Pentium 4	0.05	12163752.56	98.95	11300235.12	92.90
3	Pentium 4	0.05	12164478.67	98.95	11686679.20	96.07
4	Intel Core i7 920 (Quad core)	0.1	12046834.85	97.99	11272379.33	93.57
5	Intel Core i7 920 (Quad core)	0.1	12047842.36	98.00	11749485.96	97.52
6	Intel Core 2 Extreme X6800	0.09	12048727.00	98.01	11734951.47	97.39
7	Intel Core 2 Extreme X6800	0.09	12160673.18	98.92	11776008.86	96.83
8	Intel Core i7 Extreme Edition	0.15	12162928.27	98.94	11422999.16	93.91
9	Intel Core i7 Extreme Edition	0.15	12160661.70	98.92	11777797.37	96.85
10	Intel Core 2 Extreme QX6700	0.165	12160968.73	98.92	11864565.48	97.56
11	Intel Core 2 Extreme QX6700	0.165	12156329.05	98.89	11976902.34	98.52
12	Intel Core 2 Extreme QX6700	0.165	12160817.18	98.92	11727719.11	96.43
13	Intel Core 2 Extreme QX6700	0.165	12160965.55	98.92	11931317.99	98.11
14	Core i7-2600	0.18	12293364.46	100.00	11959913.00	97.28
15	Core i7-2600	0.18	12161210.37	98.92	12059303.00	99.16

Table 4.8: Resource Utilization after introduction of Job constraint and pricing model Workload 5 (DAS-2)

ID	Resource	Pricing model	Execution time	Makespan %age	Actual utilized time	Utilization %age
1	Pentium 4	0.05	307118.82	99.20	280545.30	91.34
2	Pentium 4	0.05	301366.18	97.34	270360.92	89.71
3	Pentium 4	0.05	300697.12	97.12	270477.22	89.95
4	Intel Core i7 920 (Quad core)	0.1	307367.74	99.28	273357.18	88.93
5	Intel Core i7 920 (Quad core)	0.1	307456.72	99.31	283748.63	92.28
6	Intel Core 2 Extreme X6800	0.09	305703.06	98.74	269904.98	88.28
7	Intel Core 2 Extreme X6800	0.09	305227.13	98.59	276089.83	90.45
8	Intel Core i7 Extreme Edition	0.15	305428.16	98.65	288772.30	94.54
9	Intel Core i7 Extreme Edition	0.15	303222.35	97.94	278433.59	91.82
10	Intel Core 2 Extreme QX6700	0.165	309606.43	100.00	291890.84	94.27
11	Intel Core 2 Extreme QX6700	0.165	309296.74	99.90	291225.75	94.15
12	Intel Core 2 Extreme QX6700	0.165	305602.29	98.71	288181.42	94.29
13	Intel Core 2 Extreme QX6700	0.165	303673.86	98.08	297436.40	97.94
14	Core i7-2600	0.18	308464.86	99.63	303151.00	98.27
15	Core i7-2600	0.18	308339.70	99.59	303203.00	98.33

4.4.5 Experiment with all constraints

In this section we have incorporated all the constraints and evaluated our scheduler on workload 7 and 8 referred in Table 4.3. Experiment is performed on 12 and 24 resources. For the sake of understanding equal number of resources for both type of jobs have been taken.

Results are given in Table 4.9, 4.10, 4.12 and 4.11. There is no big difference with the result of Table 4.8 and 4.7. In this result, it is observed that utilization percentage have dropped a little. Since jobs now have inter-resource type job dependencies utilization percentage drop is reasonable. Other performance parameter holds good.

An example of pareto front for this experiment is given in Figure 4.10

Table 4.9: Resource Utilization under all constraints on Workload DAS-2

ID	Resource	Pricing model	Execution time	Makespan %age	Actual utilized time	Utilization %age
1	Pentium 4	0.05	388054.55346	95.31	337986.508894	87.10
3	Intel Core i7 920 (Quad core)	0.1	390646.860537	95.95	362241.059321	92.72
5	Intel Core 2 Extreme X6800	0.09	391917.860219	96.26	357671.610452	91.26
7	Intel Core i7 Extreme Edition	0.15	389061.135613	95.56	367173.559685	94.37
9	Intel Core 2 Extreme QX6700	0.165	389834.143125	95.75	368452.037427	94.51
11	Core i7-2600	0.18	394967.616183	97.01	365376	92.50
2	Pentium 4	0.05	407130.811479	100.00	362875.39219	89.12
4	Intel Core i7 920 (Quad core)	0.1	406698.612175	99.89	343454.864029	84.44
6	Intel Core 2 Extreme X6800	0.09	403146.303747	99.02	348012.012859	86.32
8	Intel Core i7 Extreme Edition	0.15	402622.406754	98.89	378981.878416	94.12
10	Intel Core 2 Extreme QX6700	0.165	405572.293961	99.62	385571.358202	95.06
12	Core i7-2600	0.18	394268.616183	96.84	374894	95.08

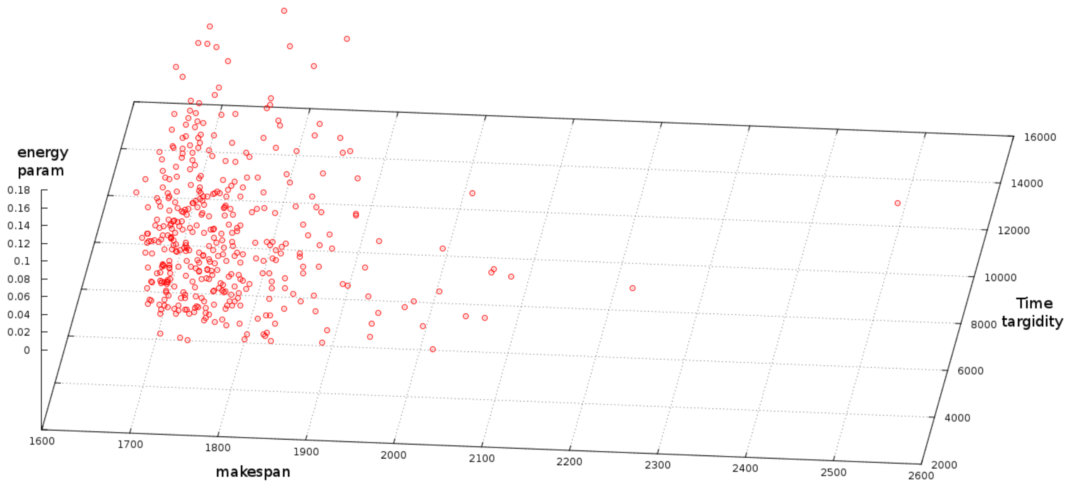


Figure 4.10: Pareto front in experiment under all constraint

Table 4.10: Resource Utilization under all constraints on Workload SHARCNET

ID	Resource	Pricing model	Execution time	Makespan %age	Actual utilized time	Utilization %age
1	Pentium 4	0.05	15856966.328786	99.65	14643863.906402	92.34
3	Intel Core i7 920 (Quad core)	0.1	15777189.495383	99.14	14224208.443954	90.15
5	Intel Core 2 Extreme X6800	0.09	15777954.142035	99.15	14347179.713218	90.93
7	Intel Core i7 Extreme Edition	0.15	15853934.301256	99.63	14962167.332284	94.37
9	Intel Core 2 Extreme QX6700	0.165	15855065.258749	99.63	14971170.083674	94.42
11	Core i7-2600	0.18	15807884.835386	99.34	14039647	88.81
2	Pentium 4	0.05	15855945.977623	99.64	15192585.514258	95.81
4	Intel Core i7 920 (Quad core)	0.1	15856889.388767	99.65	15492772.72683	97.70
6	Intel Core 2 Extreme X6800	0.09	15856577.788845	99.64	15509484.322644	97.81
8	Intel Core i7 Extreme Edition	0.15	15808788.880171	99.34	15123906.518069	95.66
10	Intel Core 2 Extreme QX6700	0.165	15913317.542563	100.00	15439774.23157	97.02
12	Core i7-2600	0.18	15884947.971385	99.82	15685884	98.74

4.5 Conclusion

The main motive of this work is to provide a flexible scheduler keeping multiple objectives into consideration. The scheduler module yields best scheduling strategies on various parameters in a pareto front. This is upto grid administrator and dynamic grid environment to choose a scheduling strategy of its choice. For experimentation purpose we have put equal weights on each objective for choosing best scheduling strategy.

Our results clearly shows that our scheduler produces optimized schedule on multi-objective optimization environment. The scheduler is scalable with resources and can process an infinite queue of jobs. The scheduler responded well with the change of constraints and behaviour of grid and job model. All resources have adhered to the makespan, and utilization rate is also high inspite of precedence constraint. It

Table 4.11: Resource Utilization under all constraints on Workload SHARCNET

ID	Resource	Pricing model	Execution time	Makespan %age	Actual utilized time	Utilization Percentage
1	Pentium 4	0.05	8243698.72	99.49	7556234.165463	91.66
2	Pentium 4	0.05	7275262.72	87.81	6253412.084217	85.95
3	Intel Core i7 920 (Quad core)	0.1	7682671.48	92.72	6326204.11	82.34
4	Intel Core i7 920 (Quad core)	0.1	8233315.82	99.37	7351339.16	89.28
5	Intel Core 2 Extreme X6800	0.09	8117606.74	97.97	7269743.03	89.55
6	Intel Core 2 Extreme X6800	0.09	8118002.88	97.98	7072373.18	87.11
7	Intel Core i7 Extreme Edition	0.15	8117468.76	97.97	7183725.78	88.49
8	Intel Core i7 Extreme Edition	0.15	8244584.64	99.50	7426916.89	90.08
9	Intel Core 2 Extreme QX6700	0.165	8117904.66	97.98	7220275.87	88.94
10	Intel Core 2 Extreme QX6700	0.165	8119335.22	97.99	7202661.19	88.70
11	Core i7-2600	0.18	8229761.81	99.33	7763631	94.33
12	Core i7-2600	0.18	8244728.91	99.51	7615311	92.36
13	Pentium 4	0.05	8119374.38	97.99	7906705.979229	97.38
14	Pentium 4	0.05	8231574.39	99.35	7705017.3826	93.60
15	Intel Core i7 920 (Quad core)	0.1	8229150.06	99.32	7628743.04	92.70
16	Intel Core i7 920 (Quad core)	0.1	8117134.83	97.97	7339766.91	90.42
17	Intel Core 2 Extreme X6800	0.09	8244402.12	99.50	7126312.76	86.43
18	Intel Core 2 Extreme X6800	0.09	8120187.28	98.00	7600934.79	93.60
19	Intel Core i7 Extreme Edition	0.15	8285650.01	100.00	8151742.16	98.38
20	Intel Core i7 Extreme Edition	0.15	8230477.53	99.33	7746832.68	94.12
21	Intel Core 2 Extreme QX6700	0.165	8232608.55	99.36	7776374.29	94.45
22	Intel Core 2 Extreme QX6700	0.165	8230191.41	99.33	7517359.04	91.33
23	Core i7-2600	0.18	8244461.91	99.50	7950420	96.43
24	Core i7-2600	0.18	8244329.91	99.50	7745014	93.94

Table 4.12: Resource Utilization under all constraints on Workload DAS-2

ID	Resource	Pricing model	Execution time	Makespan %age	Actual utilized time	Utilization Percentage
1	Pentium 4	0.05	219982.24	97.21	163440.56	74.29
2	Pentium 4	0.05	219542.01	97.02	174237.89	79.36
3	Intel Core i7 920 (Quad core)	0.1	219052.01	96.80	165654.30	75.62
4	Intel Core i7 920 (Quad core)	0.1	216803.93	95.81	184625.00	85.15
5	Intel Core 2 Extreme X6800	0.09	219223.62	96.88	182191.65	83.10
6	Intel Core 2 Extreme X6800	0.09	219492.39	97.00	174748.10	79.61
7	Intel Core i7 Extreme Edition	0.15	219025.20	96.79	181810.38	83.00
8	Intel Core i7 Extreme Edition	0.15	220180.92	97.30	188177.47	85.46
9	Intel Core 2 Extreme QX6700	0.165	224356.86	99.15	177056.99	78.91
10	Intel Core 2 Extreme QX6700	0.165	195262.07	86.29	171776.61	87.97
11	Core i7-2600	0.18	219419.10	96.97	190443	86.79
12	Core i7-2600	0.18	218241.87	96.45	199849	91.57
13	Pentium 4	0.05	218245.15	96.45	193682.53	88.74
14	Pentium 4	0.05	221455.49	97.87	179685.28	81.13
15	Intel Core i7 920 (Quad core)	0.1	220399.63	97.40	173087.60	78.53
16	Intel Core i7 920 (Quad core)	0.1	223197.97	98.64	184545.05	82.68
17	Intel Core 2 Extreme X6800	0.09	223858.93	98.93	187562.65	83.78
18	Intel Core 2 Extreme X6800	0.09	221743.64	97.99	189665.95	85.53
19	Intel Core i7 Extreme Edition	0.15	225453.79	99.63	164904.97	73.14
20	Intel Core i7 Extreme Edition	0.15	226286.04	100.00	178501.31	78.88
21	Intel Core 2 Extreme QX6700	0.165	224749.06	99.32	188318.89	83.79
22	Intel Core 2 Extreme QX6700	0.165	225663.04	99.72	184520.37	81.76
23	Core i7-2600	0.18	222377.53	98.27	196349	88.29
24	Core i7-2600	0.18	223615.40	98.82	201232	89.99

is difficult to display minimization of cost and time targidity parameter in graph or table. However a live demo of search space graph with schedules/chromosomes on successive iteration of genetic algorithm can verify its authenticity (Refer to User's Manual in Appendix A).

Chapter 5

Conclusion and Future Work

We have addressed the grid job scheduling problem with additional dimension i.e. introduced precedence constraint with heterogeneous resources and types. Scheduling jobs while keeping multiple objectives in consideration is a challenging task on a dynamic grid environment. Beyond that, scheduling in grid being a real time operation, the scheduler should produce result within few seconds or minutes. This makes scheduling more difficult.

Our resource manager simulates dynamic grid environment by adding and dropping resources. We have formularized minimization functions, created avant-garde crossover, mutation and selection operator, merged with existing technology of pareto based optimization technique. The scheduler module outputs a set of best schedules on each run and offer grid administrator a better grip in choosing a schedule compatible according to the grid environment at that moment. Job-grouping technique for fine-grained jobs keeping precedence constraint and resource constraint accelerates the yield of scheduler.

Our job scheduler have not considered some real world scenarios like transfer of jobs or input files from one cluster to another before executing it. Resources leaving grid unexpectedly have a huge impact of resource utilization and QoS given to the jobs. If scheduler somehow obtain knowledge about the behavior of resources from grid logs, MTTF(Mean Time to Failure); it can schedule accordingly. Mining grid logs and find behaviour of the resources and jobs is important in real world scenarios.

Appendix A

Job Scheduler Module User's Manual

This chapter explains how to run and configure our scheduler and its other components related to it.

A.1 System Requirements

- Intel processor / AMD processor 2.0 GHz or better, RAM: 4 GB, with 500 MB of free storage space.
- Linux OS (Ubuntu 10.10 / Fedora 13 / Linux mint or better)
- C++ library
- SSH services on resources/computers with key based login.
- MPICH2 library with hydra(mpiexec) [23]
- GNUPLOT software

A.2 Installation

Before executing the scheduler following steps are needed to be done :

- Extract “modjs.zip”

  $ tar -xvzf modjs.zip

- Compile the source code

  $ make

- Go to folder “resource”

  $ cd resource

  $ gcc -c resource_manager.c -o resource

- Enter available resource information in “initial_resource.in” in specified format.

- Copy any job file from ”data” folder and name it ”job.in” for e.g.

  $ cp data/DAS-2/job_no_pred.in job.in

- prepare hostfile.txt with ip address or domain name of all resources.

A.3 Execution

Command to run the job scheduler follows :

- mpiexec -disable-hostname-propagation -hostfile hostfile.txt ./modjsg <plot> <NUM_JOBS> <POPULATION> <GENERATION> <RANDOM_INTEGER>

- <plot> - 0 (run without GNUPLOT), 1 (without GNUPLOT)

- <NUM_JOBS> - Number of jobs to be scheduled on each run of the job scheduler module. Range [100,1000] multiplier of 4.

- <POPULATION> - Chromosome population for genetic algorithm range, Range [200,1000]

- <GENERATION> - Iteration in genetic algorithm, Range [50,300]

- <RANDOM_INTEGER> - Any integer for randomize function seed.
  e.g. $ mpiexec -disable-hostname-propagation -hostfile hostfile.txt ./modjsg 0 100 400 300 432421

- Command to run resource manager :

  $ cd resource

  $ ./resource

To configure the selection criteria of schedule after final population of efficient schedule has been generated modify weight_fun[] in report_best() function in report.c file.

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