國立交通大學

資訊科學與工程研究所

碩 士 論 文

網格環境中支援工作流程應用程式之線上即時排程方法

Online Scheduling of Workflow Applications in a Grid Environment

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中 華 民 國 九 十 八 年 九 月

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摘要

在網格環境中對工作流程應用程式排程是個很大的挑戰,因為這類型的問題是屬於 NP-complete。對於這類型問題，現今已經有許多探索式的方法被提出，然而大部份都著重在排程單一個工作流程應用程式。近幾年來，有許多的研究致力於處理並行或線上的工作流程,但在每個工作需要多顆處理器的情況這些研究沒辦法處理，本文中，我們提出了一個 OWM 方法，OWM 對線上工作流程可以有效的做排程。為了解決當工作需要多顆處理器所面臨的問題，我們加入解決這類問題的一些有名方法到 OWM 中，如：first fit，conservative backfilling，easy backfilling。根據模擬實驗，數據顯示我們所提出的 OWM 表現的比其他方法還要傑出；而在工作需要多顆處理器的情況下，OWM(FCFS)表現的幾乎和 OWM(conservative)一樣並且 OWM(FCFS)表現的比 OWM(easy)和 OWM(first fit)還要來的好。

關鍵字: 線上工作流程，不循環有向圖，工作圖，工作流程排程，工作排程，異質系統，網格計算，工作配置，資料平行，回填機制。

Online Scheduling of Workflow Applications in a Grid Environment

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Abstract

Scheduling workflow applications in a Grid environment is a great challenge, because it is NP-complete problem. Many heuristic methods are presented, but most of them work in the domain of single workflow application. In recent years, there are several heuristic methods presented to deal with concurrent workflows or online workflows, but they do not work with workflows composed of data-parallel tasks. In the thesis, we present an approach for dealing with online workflows, which is named Online Workflow Management (***OWM***). For dealing with data-parallel problems, well-known approaches, e.g., first fit, conservative backfilling and easy backfilling are added into ***OWM***. The experiments show that ***OWM*** outperforms other two methods in various workloads. For workflows composed of data-parallel tasks, the experiments show that ***OWM***(***FCFS***) is almost equal ***OWM***(***conservative***), and outperforms ***OWM***(***easy***) and ***OWM***(***first fit***).

Keywords: Online Workflows, DAG, Task Graph, Workflow Scheduling, Task Scheduling, Heterogeneous Systems, Grid Computing, Task Allocation, Data Parallel Task, Backfilling.

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Chapter 1 Introduction

Grid environments are an important platform for running high-performance and distributed applications. Many large-scale scientific applications are usually constructed as workflows due to large amounts of interrelated computation and communication, e.g., Montage [29] and EMAN [30]. A Grid environment is composed of widespread resources from different administrative domains. Miguel et al. [33] indicates that a Grid environment usually has the characteristics: heterogeneity, large scale and geographical distribution. Task scheduling in Grid is a NP-complete problem [31] [32], therefore many heuristic methods have been proposed. The workflow scheduling problem in Grid environments is a great challenge. In the past years, there are many static heuristic methods proposed [3] [4] [5] [6] [7] [8] [9] [18] [25]. They are designed in the domain of scheduling single workflow only.

Zhao et al. presented composition and fairness approaches [20] for scheduling multiple workflows at the same time. T. N'takpe' et al. presented an approach [23] to scheduling concurrent workflows composed of moldable tasks. However, all these methods do not work with online workflows: i.e., multiple workflows occur at different times. Z. Yu et al. [21] presented a planner-guided dynamic scheduling approach for dealing with online workflows, but it doesn't work with workflows composed of data-parallel tasks (parallel tasks) of which each uses multiple processors simultaneously for its execution.

In this thesis, we present a new approach called Online Workflow Management (***OWM***). There are four processes in ***OWM***: Critical Path Workflow Scheduling (CPWS), Task Scheduling, Multi-Processor Task Rearrangement and Adaptive Allocation (AA). CPWS process submits tasks into the waiting queue. Task

scheduling and AA processes prioritize the tasks in the queue and assign the task with highest priority to the processor for execution respectively. In data-parallel task scheduling, there may be some scheduling holes which are formed when the free processors are not enough for the first task in the queue. The multi-processor rearrangement process works for dealing with scheduling holes to improve utilization. The process includes first fit, easy backfilling [22], and conservative backfilling [22] approaches.

To validate the advantages of the cooperation designed among these four processes, task-waiting queue, event queue and workflows, we developed a Grid simulator using a discrete-event based technique for experiments. Task-waiting queue and event queue keep the tasks and events for processing. The Grid environment consists of several simulated clusters of which each contains an amount of processors. A workflow is represented by direct acyclic graph (DAG). Each experiment involves 20 runs, and each run has 100 unique DAGs on a Grid environment that contains 3 clusters each containing 30~50 processors respectively. Experimental results show that ***OWM*** has better performance than ***RANK_HYBD*** [21] and ***Fairness_Dynamic*** which extends the Fairness (F2) in [20] to handle online workflows. When workflows composed of data-parallel tasks, the experimental results show that ***OWM***(***FCFS***) is almost equal to ***OWM***(***conservative***), and outperforms ***OWM***(***easy***) and ***OWM***(***first fit***).

The remainder of the thesis is organized as follows. Chapter 2 discusses related work. Chapter 3 describes the software simulator for workflow scheduling. Chapter 4 presents the ***OWM*** approach for Grid environments. Chapter 5 presents the experimental results and Chapter 6 concludes the thesis.

Chapter 2 Related Work

In this chapter, we survey related algorithms in Grid environments. Section 2.1 describes workflow scheduling algorithms for Grid computing. Section 2.2 describes static workflow scheduling algorithms. Section 2.3, 2.4, 2.5 describe concurrent workflows, online workflow and mixed parallel workflows scheduling algorithms in Grid environments respectively.

2.1 Workflow Scheduling Algorithms for Grid Computing

Workflow scheduling algorithms for Grid computing can be classified into two groups [26] (Figure 2-1): static and dynamic.

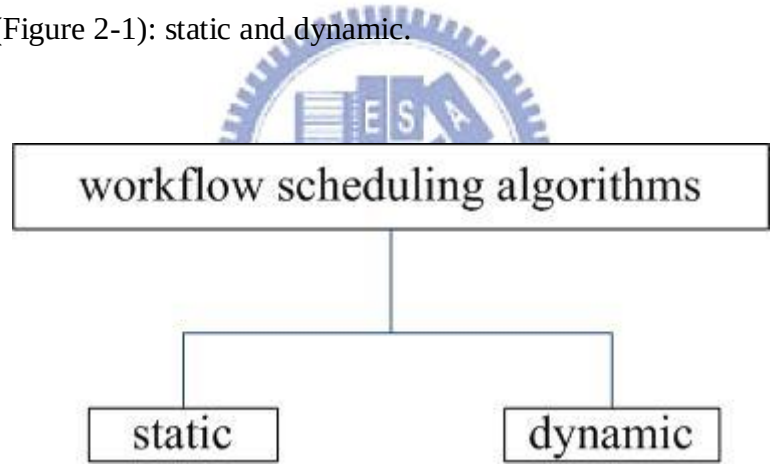


Figure 2-1 A taxonomy of workflow scheduling algorithms

In a static scheduling algorithm, the structure of workflow applications i.e., the dependency of tasks, and the estimated cost are known in the very beginning. The resource assignment of tasks is made before execution (Figure 2-2), and each approach has its own policy of assignment. Static approaches are not adaptive to some situations, e.g., one of the resources selected fails, or the real execution time on some resources is longer than the estimated time. Unfortunately, these situations occur in a great potential due to the nature of Grid environments. To alleviate this problem, there

are two approaches: task partitioning [10] and rescheduling [1] [11]. The former partitions a workflow into multiple sub-workflows which are executed sequentially. Instead of mapping entire workflow at one time, it allocates resources to tasks in one sub-workflow each time. A sub-workflow mapping is started only after the previously mapped sub-workflow starts the execution. The latter reschedule unexecuted tasks when the Grid environment changes. H. Braun et al. compare eleven static heuristic algorithms on heterogeneous distributed computing systems [2]. Figure 2-2 shows an example of a static scheduling algorithm. Figure 2-2(a) shows an original workflow. Figure 2-2(b) shows the resource mapping of tasks before execution: t1, t3 and t5 are mapped to R1, and t2 and t4 are mapped to R2 .

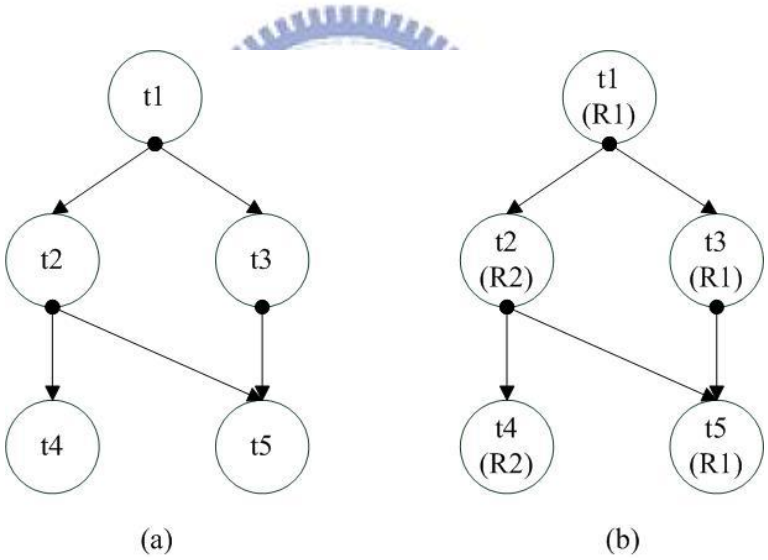


Figure 2-2 An example of static scheduling (a) an original workflow (b) the resource mapping of a workflow before execution

Dynamic scheduling approaches perform task allocation as workflow applications execute. When a task is ready to execute, it is submitted to waiting queue. Dynamic scheduling mechanisms make a decision when the waiting queue has tasks and there are free resources. Dynamic scheduling is usually applied when it is difficult

to estimate the costs of tasks, or when workflow applications may come at different times (it is called online scheduling). For example, Z. Yu [21] proposed a planner-guided scheduling strategy.

2.2 Static Workflow Scheduling Algorithms

Static workflow scheduling algorithms can be classified into two groups [17] as shown in Figure 2-3: heuristic-based and meta-heuristic based.

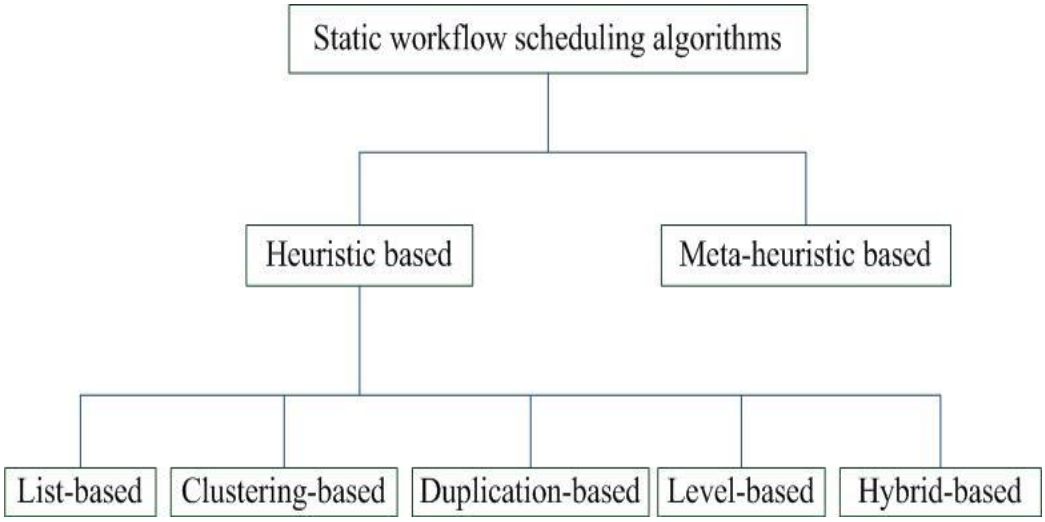


Figure 2-3 A taxonomy of static workflow scheduling algorithms

Heuristic-based scheduling algorithms usually can be classified into five groups: (1) list-based, (2) clustering-based, (3) duplication-based, (4) level-based, (5) hybrid-based. A list-based heuristic approach maintains a list of all tasks of a workflow application according to their priorities. The method schedules the tasks based on the list. There are list-based heuristics proposed [3] [4] [5] [6] [7].

HEFT (Heterogeneous Earliest Finish Time) [7] is a well-known list-based

scheduling algorithm in heterogeneous environments, and it is implemented in ASKLON that is a workflow management system based on Grid computing [17]. In recent years, many researches have been applied to modify HEFT in the corresponding environments. Typical examples include HHS (Hybrid Scheduling Algorithm) [18], M-HEFT (Mixed-Parallel HEFT) [19], Fairness Policy [20] , RANK_HYBD [21].

HEFT algorithm has two major phases: a task prioritizing phase and a processor selection phase. The task prioritizing sets the priority of each task with an upward rank value, $rank_u$, which is based on mean computation and mean communication costs. A higher $rank_u$ value gets a higher priority. The processor selection selects a processor which has earliest estimated finish time of the task. Figure 2-4 shows an example of a list-based heuristic, HEFT.

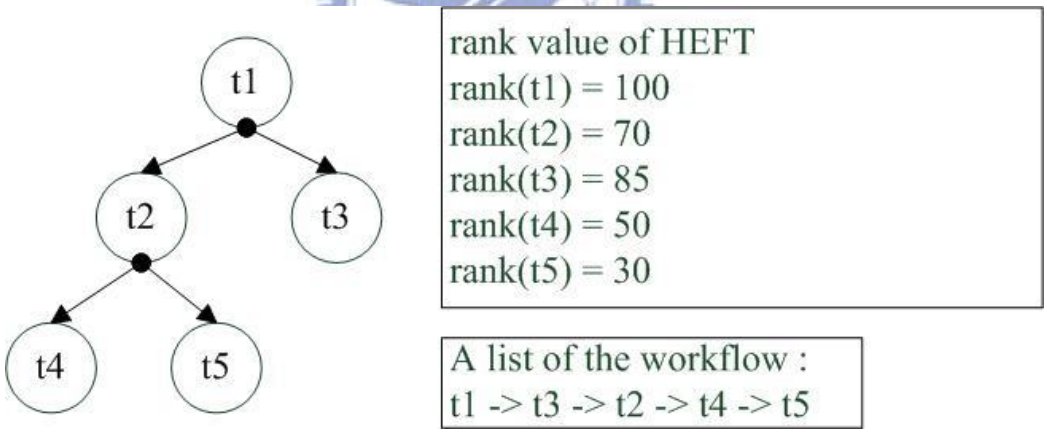


Figure 2-4 An example of a list-based heuristic

The main idea of clustering-based heuristic method is to reduce communication delay by grouping the tasks of heavy communicating into the same labeled cluster. In general, a clustering-based heuristic method has two phases: clustering and merging. In the clustering phase, the original workflow application is partitioned into clusters, and the merging phase merges the clusters so that the remaining number of clusters

equals to the number of resources. There are various clustering-based heuristic methods proposed [8]. Figure 2-5 shows an example of a clustering-based heuristic. In figure 2-5, (a) represents an original workflow, and (b) shows the result of arranging the tasks into three clusters {t1, t2, t7}, {t3, t4, t6}, {t5}. These three clusters {t1, t2, t7}, {t3, t4, t6}, {t5} will be allocated to three resources respectively at run time.

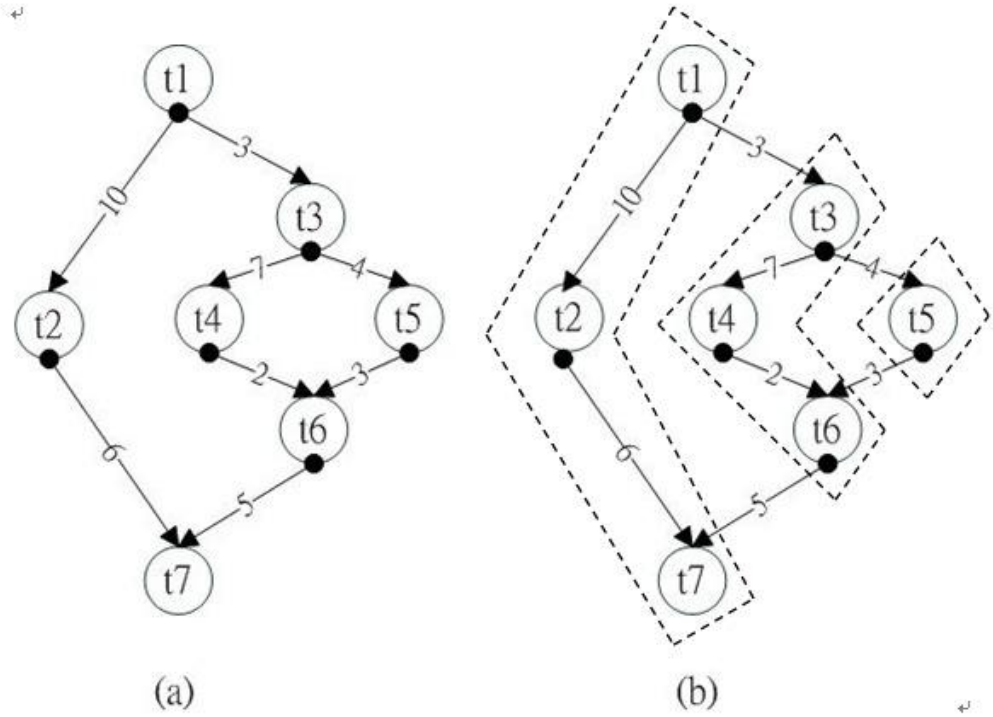


Figure 2-5 An example of a clustering-based heuristic (a) an original workflow (b) after clustering

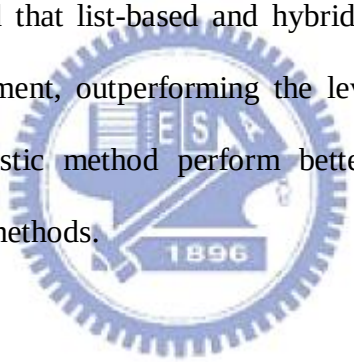
A duplication-based heuristic method helps a task to transmit the data to the resource of succeeding task(s) implicitly during its execution time. This may reduce the communication cost from a task to a successor. Various duplication-based heuristic methods are proposed [9].

A level-based heuristic method, i.e. LHBS (Levelized Heuristic Based Scheduling) [25], divides the workflow into levels of independent tasks. Within each

level, LHBS can use Greedy, Min-Min, Min-Max, or Sufferage [2] heuristics to map the tasks to resources. Both the GrADS [16] and Pegasus [27] schedulers use a version of LHBS.

A Hybrid-based heuristic method, i.e., HHS (Hybrid Heuristic Scheduling) [18], is a combination of list-based and level-based heuristic methods. HHS first computes the levels as in LHBS, then the tasks in each level following the prioritized order used by HEFT. The five static heuristic methods mentioned above are restricted to single workflow.

Y. Zhang et al. [24] compare HEFT [7], LHBS [25], and HHS [18] in Grid environments. They showed that list-based and hybrid-based heuristic methods are effective in a Grid environment, outperforming the level-based heuristic. [15] also shows that list-based heuristic method perform better than clustering-based and duplication-based heuristic methods.



The meta-heuristic based scheduling algorithms produces an optimized scheduling solution based on the performance of the entire workflow. Genetic algorithms [13], simulated annealing [14], and GRASP (Greedy randomized adaptive search) [12] are well-known meta-heuristic scheduling algorithms. Each task in the workflow is assigned a priori to resources in order to minimize the makespan of the whole workflow. However, the scheduling time in meta-heuristic scheduling algorithms is significantly higher [16] [17] than heuristic-based algorithms.

J. Blythe et al. [16] compare the heuristic-based algorithm and the meta-heuristic based algorithm. In the comparison, they select one algorithm to represent each approach, Min-Min scheduling algorithm for heuristic-based algorithm and GRASP

for the meta-heuristic based algorithm. The experiment results indicate both approaches are similar for compute-intensive cases, but the meta-heuristic based algorithm is better than the heuristic-based algorithm for data-intensive cases. However, the time complexity of the meta-heuristic based algorithm grows more rapidly than the heuristic-based algorithm if the workflow has more tasks.

2.3 Scheduling Concurrent Workflows in Grid Environments

In the past years, most works dealing with workflow scheduling were restricted to single workflow application. Zhao et al. [20] envisaged a scenario that need to schedule multiple workflow applications at the same time. They proposed two approaches: composition approach and fairness approach.

(1) The composition approach merges multiple workflows into a single workflow first. Then, two list scheduling heuristic methods, such as HEFT [7] and HHS [18], can be used to schedule the merged workflow.

(2) The main idea of fairness approach is that when a task completes, it will re-calculate the slowdown value of each workflow (or single workflow) against other workflows and make a decision on which a workflow should be considered next.

Moreover, the composition and the fairness approaches are static algorithms and not feasible to deal with online workflow applications, i.e., multiple workflows come at different times.

2.4 Scheduling Online Workflows in Grid Environments

RANK_HYBD [21] is designed to deal with online workflow applications submitted by different users at different times. The task scheduling approach of RANK_HYBD sorts the tasks in *waiting queue* using the rules repeatedly.

1. If tasks in *waiting queue* come from multiple workflows, the tasks are sorted in ascending order of their rank value ($rank_u$) where $rank_u$ is described in HEFT [7];
2. If all task are belong to the same workflow, the tasks are sorted in descending order of their rank value ($rank_u$).

However, the number of processors to be used by each task is limited to a single processor. It is not feasible to deal with workflows composed of data-parallel tasks.

2.5 Scheduling Mixed Parallel Workflows in Grid Environments.

Parallel task scheduling can be classified into two modes: rigid and moldable. The number of processors required by a rigid task is fixed. The number of processors used in a moldable task is determined by some algorithms before each run.

T. N'takpe' et al. proposed mixed parallel applications on Heterogeneous platforms [28]. This can be considered as an example of moldable mode. Mixed parallelism is a combination of task parallelism and data parallelism where the former indicates that an application has more than one task that can execute concurrently and the latter means a task can run at different resources concurrently.

[28] is only suitable for a single workflow. T. N'takpe' et al. further developed an approach to deal with concurrent mixed parallel applications [23]. Concurrent scheduling for mixed parallel applications contains two steps: constrained resource allocation and concurrent mapping. The former aims at finding an optimal allocation

for each task. The number of processors is determined in this step. The latter prioritizes tasks of workflows.

However, the approach in [23] is restricted to concurrent workflows. It is infeasible to deal with online workflows.

Chapter 3 Software Simulator for Workflow Scheduling

This chapter presents the software simulator that we developed for simulating the workflow scheduling activities in a Grid environment. Section 3-1 describes data components in the simulator. Section 3-2 describes classes used in the simulator and section 3-3 presents simulation processes.

3.1 Data Components in the Simulator

Input Workload:

A workflow application is represented by a direct acyclic graph (DAG). A DAG is defined as G = (V, E), where V is a set of nodes, each representing a task, and E is the set of links, each representing the computation precedence order between two tasks. For example, a link $(x,y) \in E$ represents the precedence constraint that task t_x completes before task t_y starts.

Global System Time (GST):

In a discrete-event based simulation, the simulator maintains a global timing system which increments the time whenever an event is processed.

System Queues:

There are two system queues: an event queue and a waiting queue. They keep the events and tasks waiting for processing.

Grid Environment:

A Grid is composed of several clusters. A cluster contains an amount of processors. The Grid is heterogeneous in that the processors at different clusters might run at different speed. On the other hand, each cluster is homogeneous, consisting of identical processors. The cost for a task includes computation and communication costs where the former means the execution time, and the latter means the data transfer time between processors. The computation cost of a task is the same for different processors in the same cluster, but may be different in different clusters. The communication cost between any two processors in the same cluster is set to be zero, but not in different clusters. Figure 3-1 shows an example of a Grid environment in our simulator. The processor speeds and network link speeds are homogeneous in the same cluster, but they are heterogeneous between different clusters.

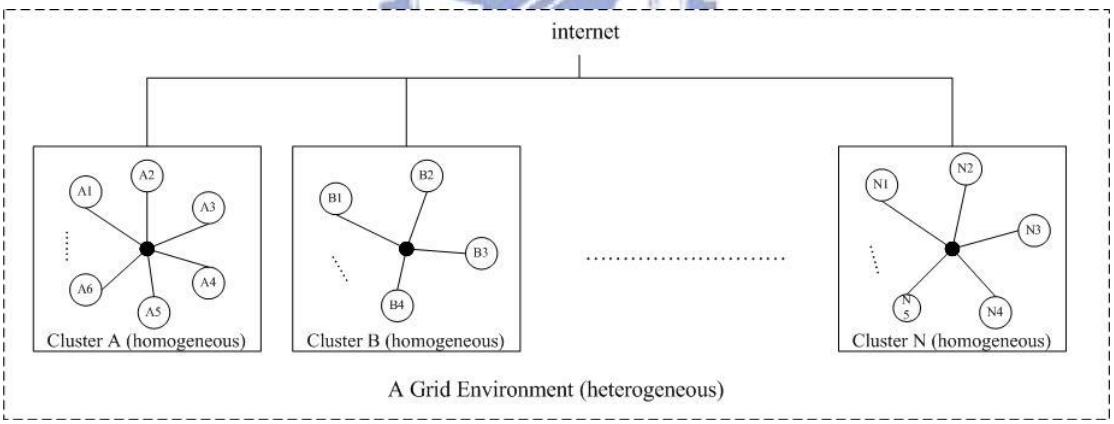


Figure 3-1 A Grid Environment

3.2 Classes in the Simulator

In this section, the classes used in the simulator are described including DAG_Generator, EventNode, EventQueue, WaitQueueNode, WaitQueue, WorkflowScheduling and Allocation classes.

DAG_Generator:

DAG_Generator is responsible for generating input workload consisting of a sequence of DAGs in their arrival order. Table 3-1 shows an UML DAG_Generator class. It contains 7 attributes, <Node, Shape, OutDegree, CCR, BRange, WDAG, Cluster>, and 4 operations, <Generator(), ShapeGenerator(Node, Shape), RelationGenerator(Node, OutDegree), CostGenerator(Node, BRange, WDAG, Cluster, CCR)>.

Table 3-1 DAG_Generator class

DAG_Information
+Node : unsigned int +Shape : double +OutDegree : unsigned int +CCR : double +BRange : double +WDAG : unsigned int +Cluster : unsigned int
+Generator(in Node : unsigned int, in Shape : double, in OutDegree : unsigned int, in CCR : double, in BRange : double, in WDAG : unsigned int, in Cluster : unsigned int) +ShapeGenerator(in Node : unsigned int, in Shape : double) +RelationGenerator(in Node : unsigned int, in OutDegree : unsigned int) +CostGenerator(in Node : unsigned int, in BRange : double, in WDAG : unsigned int, in Cluster : unsigned int, in CCR : double)

The attributes and operations in DAG_Generator are described as following.

Attributes:

1. Node: the number of tasks in a DAG.
2. Shape: the shape of a DAG.
3. OutDegree: the maximum of out degree of tasks in a DAG.
4. CCR: communication cost to computation cost ratio.
5. BRange (β): distribution range of computation cost of tasks on processors. It is the heterogeneous factor for processor speeds. A high range indicates

significant differences in task's computation costs among the processors and a low range indicates that the expected execution time of a task is almost the same on each processor.

6. WDAG: the average computation cost of a DAG.
7. Cluster: the number of clusters in a Grid environment.

Operations:

1. Generator(): randomly generates a DAG according to the 7 input parameters mentioned above. It invokes ShapeGenerator(), RelationGenerator(), CostGenerator() in turn.
2. ShapeGenerator(Node, Shape): generates the shape of a DAG using Node and Shape parameters. The height (depth) of a DAG is randomly generated from a uniform distribution with mean value equal to $\frac{\sqrt{\text{Node}}}{\text{Shape}}$. The width for each level is randomly generated from a uniform distribution with mean value equal to $\text{Shape} \times \sqrt{\text{Node}}$. If $shape \gg 1$, it generates a shorter graph with high parallelism degree. Otherwise, if $\text{shape} \ll 1$, it generates a longer graph with a low parallelism degree.
3. RelationGenerator(Node, OutDegree): generates the connect relation of a DAG according to the input parameters Node and OutDegree defined above. Out degree of each task is randomly generated from a uniform distribution with range $[1, \text{OutDegree}]$.
4. CostGenerator(Node, BRange, WDAG, Cluster, CCR): generates the computation cost and the communication cost of a DAG. The average estimated computation cost of each task t_x, i.e., $\overline{w_x}$ is randomly generated from a distribution ranged $[1, 2 \times \text{WDAG}]$. The estimated computation cost of each

task t_x on each cluster c_y, i.e., $w_{x,y}$ is randomly generated from a uniform distribution with range:

$$\overline{w_x} \times (1 - \frac{BRange}{2}) \leq w_{x,y} \leq \overline{w_x} \times (1 + \frac{BRange}{2})$$

EventNode:

EventQueue stores a set of EventNodes. Each EventNode contains 6 attributes, <type, time, jobIndex, dagIndex, *pre, *next>. Table 3-2 shows EventNode class.

Table 3-2 EventNode class

EventNode
+type : EventType +time : unsigned long +jobIndex : unsigned long +dagIndex : unsigned long +*pre : EventNode +*next : EventNode

Attributes:

1. type: the type of an event. Table 3-3 shows EventType enumeration. There are two kinds of EventType: submit and end. Each event contains the attributes, <jobIndex, dagIndex> uniquely identifying a job. When a submit event occurs, a job <jobIndex, dagIndex> will be submitted to WaitQueue for scheduling and allocation. When an end event occurs, a job <jobIndex, dagIndex> completes successfully.

Table 3-3 EventType enumeration

<<enumeration>> **EventType**
+submit +end

2. time: the time that the event happens.
3. jobIndex: the index of a job.
4. dagIndex: the index of a dag.
5. *pre: a link pointing to the preceding EventNode.
6. *next: a link pointing to the next EventNode.

EventQueue:

EventQueue is composed of a sequence of EventNodes. There are 3 attributes, <*front, *rear, eventQueueCount>, and 3 operations, <enQueue(EventNode), deQueue(), isEmpty()> in EventQueue. Table 3-4 shows EventQueue class.

Table 3-4 EventQueue class

EventQueue
+*front : EventNode +*rear : EventNode
+enQueue(in enNode : EventNode) +deQueue() : EventNode +isEmpty() : bool

Attributes:

1. *front: points to the first EventNode in EventQueue.
2. *rear: points to the last EventNode in EventQueue.

Operations:

1. enQueue(EventNode): an operation that inserts an EventNode into EventQueue.
2. deQueue(): an operation that removes and returns the first EventNode in EventQueue.

3. isEmpty(): an operation that checks whether EventQueue is empty or not. If EventQueue is empty, it returns true. Otherwise, it returns false.

Figure 3-2 shows an example of EventQueue. The EventNodes are sorted according to their arrival time (EventNode.time). *fornt points to the first EventNode, EventNode1, and *rear points to the last EventNode, EventNode5.

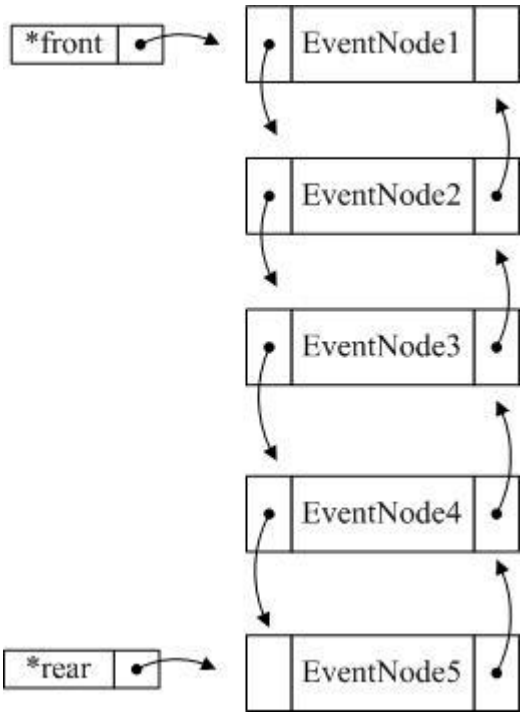


Figure 3-2 An example of EventQueue

WaitQueueNode:

WaitQueueNode represents the elements stored in WaitQueue. There are 7 attributes, <jobIndex, dagIndex, np, ftown, ftmulti, rank, slowdown> in WaitQueueNode. Table 3-5 shows WaitQueueNode class.

Table 3-5 WaitQueueNode class

WaitQueueNode
+jobIndex : unsigned long +dagIndex : unsigned long +np : unsigned long +ftown : unsigned long +ftmulti : unsigned long +rank : unsigned long +slowdown : double

Attributes:

1. jobIndex: the index of a job.
2. dagIndex: the index of a dag.
3. np: the number of processors that the job <jobIndex, dagIndex> needs.
4. ft_{own}: the finish time of the job <jobIndex, dagIndex>, when the DAG has the whole processors for exclusive use. The detail of ft_{own} is described in [20].
5. ft_{multi}: the finish time of the job <jobIndex, dagIndex>, when the DAG is scheduled onto processors along with other workflow applications. The detail of ft_{multi} is described in [20].
6. rank: the upward rank value $rank_u$. $rank_u(t_i)$ means the length of critical path from task t_i to the exit task. The detail of $rank_u$ is described in Chapter 4.
7. slowdown: the main idea of the slowdown value is defined as ft_{own} / ft_{multi}. The detail of slowdown is described in [20].

WaitQueue:

WaitQueue is composed of a sequence of WaitQueueNodes. On a submit event, a new WaitQueueNode is created according to the EventNode, and is submitted to WaitQueue by calling WaitQueue.enQueue (WaitQueueNode) operation. WaitQueue has 2 attributes, <waitQueueCount, waitQueue[]>, and 10 operations, <enQueue(WaitQueueNode), remove(WaitQueueNode), isEmpty(), front(), Fairnss_TaskScheduling(), RankHYBD_TaskScheduling(), Easy_Backfilling(), Conservative_Backfilling(), FirstFit(), FCFS()>. Table 3-6 shows WaitQueue class.

Table 3-6 WaitQueue class

WaitQueue
+waitQueueCount : unsigned long +waitQueue[] : WaitQueueNode
+enQueue(in enNode : WaitQueueNode) +remove(in deNode : WaitQueueNode) +isEmpty() : bool +front() : WaitQueueNode +Fairness_TaskScheduling() +RankHYBD_TaskScheduling() +Conservative_Backfilling() +Easy_Backfilling() +FirstFit() +FCFS()

Attributes:

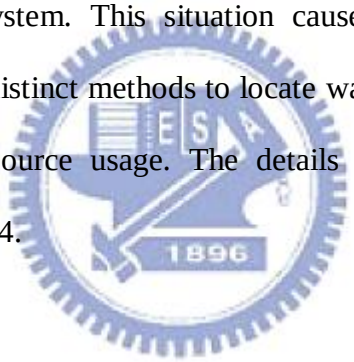
1. waitQueueCount: the total number of WaitQueueNodes in WaitQueue. In other words, it represents the length of WaitQueue.
2. waiQueue[]: an array that WaitQueueNodes are stored.

Operations:

1. enQueue(WaitQueueNode): an operation that inserts a WaitQueueNode into WaitQueue.
2. remove(WaitQueueNode): an operation that removes a WaitQueueNode from

WaitQueue.

3. isEmpty(): an operation that checks whether WaitQueue is empty or not. If WaitQueue is empty, it returns true. Otherwise, it returns false.
4. front(): returns the first WaitQueueNode in WaitQueue.
5. Fairness_TaskScheduling() and RankHYBD_TaskScheduling(): both operations implement two distinct task scheduling algorithms. The order of WaitQueueNodes in WaitQueue is determined by these two operations. The details of these two scheduling algorithms will be described in Chapter 4.
6. Easy_Backfilling(), Conservative_Backfilling() and FirstFit(): In parallel task scheduling, a task is delayed when the processors it needs are more than free processors in the system. This situation causes a scheduling hole. These approaches provide distinct methods to locate waiting tasks for the scheduling hole to improve resource usage. The details of these algorithms will be described in Chapter 4.



Workflow Scheduling:

Workflow Scheduling implements workflow scheduling algorithms and contains 2 operations, <SWS(), CPWS()>. SWS means simple workflow scheduling, and CPWS means critical path workflow scheduling. The detailed descriptions of these two workflow scheduling algorithms are presented in Chapter 4. Table 3-1 shows WorkflowScheduling class.

Table 3-7 WorkflowScheduling class

WorkflowScheduling
+SWS() +CPWS()

Allocation:

Allocation implements allocation algorithms and contains 2 operations, <SA(), AA()>. SA means simple allocation, and AA means adaptive allocation. The detailed description of these two allocation algorithms are presented in Chapter 4. Table 3-8 shows Allocation class.

Table 3-8 Allocation class

Allocation
+SA() +AA()

3.3 Simulation Process

This section presents the simulation process. The GST cannot change until an event happens. The simulation process contains several procedures including Task_Submission(), Scheduler_Allocation() and Simulator(), where the former two are invoked in Simulator(). The following describes the details.

Simulator():

Simulator() is the skeleton procedure of our simulator. Procedure 3-1 shows the pseudo code of Simulator(). Firstly, it constructs a Grid environment, generates input DAGs using DAG_Generator.Generator(), and then calls Task_Submission(), as shown in lines 2 to 4. Line 5 checks whether EventQueue is empty or not. If EventQueue is empty, the simulation completes successfully. Otherwise, the simulator takes the first Node in EventQueue as EventNode, and sets GST with EventNode.time as shown in lines 6 to 7. Lines 8 to 10 show that when the EventNode is a submit event, a WaitQueueNode is created and added into WaitQueue correspondingly. Lines 11 to 13 show that if the EventNode is an end event, it will release the processors that the EventNode requires, and calsl Task_Submission() to check if there are tasks need to be submitted. Line 14 checks whether GST is equal to the time of the first node in EventQueue or not. If it is equal, the simulator goes to loop the above execution. Otherwise, it calls Scheduler_Allocation() to schedule the tasks in the waiting queue and allocate the tasks.

Scheduler_Allocation():

Scheduler_Allocation() sorts waiting queue (WaitQueue.WaitQueue[]) according to the task scheduling algorithm, and allocates a task to the free processor according to the allocation algorithm. Procedure 3-2 shows the pseudo code of

Scheduler_Allocation(). According to the task scheduling algorithm used, WaitQueue.Fairness_TaskScheduling() or WaitQueue.RankHYBD_TaskScheduling() can be selected to prioritize tasks in waiting queue as shown in line 2. Line 3 checks the waiting queue whether is empty or not. If the waiting queue is empty, the procedure finishes. Otherwise, it executes the following codes. If workflows composed of data-parallel tasks, scheduling holes may happen. To overcome this problem for improving processor usage, the multi-processor task rearrangement algorithm can be selected: WaitQueue.FCFS(), WaitQueue.FirstFit(), WaitQueue.Conservative_Backfilling or WaitQueue.Easy_Backfilling, as shown in lines 4 to 6. Lines 7 to 8 show that the system takes the first node in the waiting queue as WaitQueueNode, and allocates the WaitQueueNode to the processors that it requires using an allocation algorithm: Allocation.SA() or Allocation.AA(). After the WaitQueueNode be allocated successfully, it is removed from the waiting queue as shown in line 10. When the WaitQueueNode completes successfully, an EventNode is created correspondingly. Then, it will be added to EventQueue with an end event as shown in lines 11 to 12.

Task_Submission():

Procedure 3-3 shows the pseudo code of Task_Submission(). Different workflow scheduling algorithms can be used, i.e., WorkflowScheduling.SWS() or WorkflowScheduling.CPWS() as shown in line 2. The detail of these two workflow scheduling algorithm is described in Chapter 4. Line 3 shows that the submitted tasks that workflow scheduling algorithm determine will cause submit events be added into EventQueue.

```
Simulator()
01  begin
02     construct a Grid environment;
03     generate online DAGs using DAG_Generator.Generator();
04     Task_Submission();

05    while( EventQueue.isEmpty() == false ) do
06              EvnetNode = EventQueue.deQueue();
07              GST = EventNode.time;
08              if( EventNode.type == submit )
09                    WaitQueueNode is created according to EventNode;
10                    WaitQueue.enQueue( WaitQueueNode );
11              else // EventNode.type == end
12                    release the processors that EventNode requires;
13                    Task_Submission();

14              if( (*EventQueue.front).time  ≠  GST)
15                    Scheduler_Allocation();
16              end if
17     end while
18  end
```

Procedure 3-1. Simulator()

```
Scheduler_Allocation()
01  begin
02      // according to the task scheduling algorithm
        WaitQueue.Fairness_TaskScheduler() or
        WaitQueue.RankHYBD_TaskScheduler();
03      while( WaitQueue.isEmpty() == false ) do
04          if (workflows composed of data-parallel tasks)
05              // according to the multi-processor task rearrangement
                WaitQueue.FCFS() or WaitQueue.FirstFit() or
                WaitQueue.Conservative_Backfilling() or
                WaitQueue.Easy_Backfilling();
06          end if
07          WaitQueueNode = WaitQueue.front();
08          // according to the allocation algorithm
            Allocation.SA() or Allocation.AA();
09          if (allocate WaitQueueNode successfully)
10              WaitQueue.remove(WaitQueueNode);
11              EventNode is created according WaitQueueNode;
12              EventQueue.enQueue(EventNode);    // end event
13          end if
14      end while
15  end
```

Procedure 3-2. Scheduler_Allocation()

```
Task_Submission()
01  begin
02      // according to the workflow scheduling algorithm
        WorkflowScheduling.SWS() or WorkflowScheduling.CPWS();

03      /* the submitted tasks that workflow scheduling algorithm determine
           will cause submit events be added into EventQueue */
        EventQueue.enQueue( EventNode );    // submit event
04  end
```

Procedure 3-3. Task_Submission()

Chapter 4 Online Workflow Management in a Grid Environment

In this chapter, we propose an ***Online Workflow Management system*** (***OWM***) for dealing with the simulation of online workflows in a Grid environment. Section 4.1 describes the structure of ***OWM***. Section 4.2 presents the proposed algorithms for ***OWM***

4.1 Structure of Online Workflow Management

Figure 4-1 shows the structure of ***OWM***. In ***OWM***, there are four processes: ***Critical Path Workflow Scheduling*** (***CPWS***), Task Scheduling, multi-processor task rearrangement and ***Adaptive Allocation*** (***AA***), and three data structures: online workflows, a Grid environment and a waiting queue. The processes are represented by solid boxes, and the data structures are represented by dotted boxes.

The four processes in ***OWM*** are independent. When workflows come into the system or tasks complete successfully, ***CPWS***, takes the critical path in workflows into account, and submits the tasks of online workflows into the waiting queue. The details of ***CWPS*** are described in section 4.2. The task scheduling process in ***OWM*** is RANK_HYBD [21]. In RANK_HYBD, the task execution order is sorted based on the length of tasks' critical path. If all tasks in the waiting queue belong to the same workflow, they are sorted in the descending order. Otherwise, the tasks in different workflows are sorted in the ascending order. In parallel task scheduling, there may be some scheduling holes which are formed when the free processors are not enough for the first task in the queue. A multi-processor rearrangement process in ***OWM*** works for scheduling holes to improve utilization. Existing techniques for the process

include first fit, easy backfilling [22] or conservative backfilling [22] approaches. When there are free processors in the Grid environment, ***AA*** gets the first task (the highest priority task) in the waiting queue, and selects the required processors to execute the task. The details of ***AA*** are described in section 4.2.

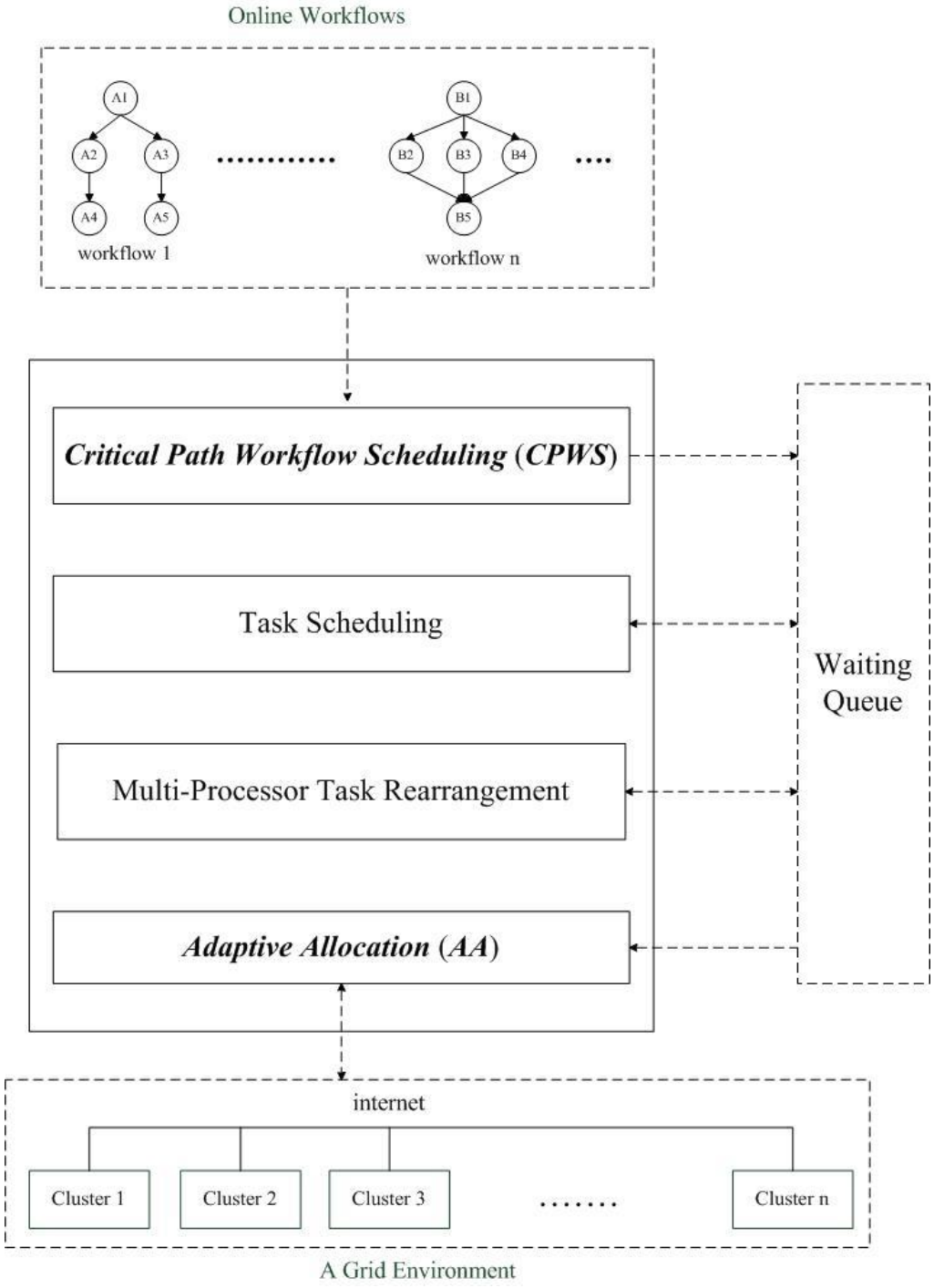


Figure 4-1 Online Workflow Management (OWM)

4.2 Online Workflow Management (OWM)

4.2.1 Upward Rank Value

The upward rank of a task t_i. $rank_u(t_i)$ [7] is the length of critical path form task t_i to the exit task. The definition as below

$$rank_u(t_i) = \overline{w_i} + \max_{t_j \in succ\,(t_i)}(\overline{c_{i,j}} + rank_u(t_j))$$

, where $succ(t_i)$ is the set of immediate successors of task t_i, $\overline{c_{i,j}}$ is the average communication cost of edge (i, j), and $\overline{w_i}$ is the average computation cost of task t_i. The computation of a rank starts from the exit task and traverses up along the task graph recursively. Thus, the rank is called upward rank, and the upward rank of the exit task t_{exit} is

$$rank_u(t_{exit}) = \overline{w_{exit}}$$

4.2.2 Critical Path Workflow Scheduling (CPWS)

A task has four states: *finished*, *submitted*, *ready* and *unready*. A *finished* task means the task has completed its execution successfully. A *submitted* task means the task is in the waiting queue. A task is *ready* when all necessary predecessor(s) of the task have finished. It is not, otherwise; the task is *unready*.

Workflow scheduling in RANK_HYBD [21] is straightforward. It submits the ready tasks into the waiting queue and is named ***Simple Workflow Scheduling*** (***SWS***). On the other hand, when a new workflow arrives, ***CPWS*** is adopted to calculate $rank_u$ of each task in the workflow and sort and put in a list for the tasks in descending order of $rank_u$. The list is named as a critical path list. The system maintains an array List[], and List[$workflow_i$] points to the critical path list of $workflow_i$. ***CPWS*** is described in Algorithm 4-1.According to the order in each critical path list, ***CPWS*** continuously submits the ready tasks in a list into the waiting queue until running into an unready task.

D: a set of unfinished workflows
List[]:an array of critical path lists. List[$workflow_i$] keeps the critical path list of $workflow_i$

CPWS(D,List[])
1 **begin**
2 **while**($D \neq \emptyset$) **do**
3 **for** each $workflow_i \in D$ **do**
4 according to the order List[$workflow_i$], continuously submit the ready tasks into the waiting queue until running into an unready task;
5 **end while**
6 **end**

Algorithm 4-1. CPWS algorithm

Figure 4-2 and 4-3 shows the difference between ***SWS*** and ***CPWS***. Figure 4-2 shows an example of ***SWS***. Black nodes are finished tasks, i.e., A1, A2, B1 and B3. White nodes are ready tasks, i.e., A3, A4, B2 and B4. White nodes with dotted lines are unready tasks, i.e., A5 and B5. ***SWS*** submits all ready tasks into the waiting queue, i.e., A3, A4, B2 and B4. Figure 4-3 shows an example of ***CPWS***. The critical path list of each workflow is sorted in descending order of $rank_u$. The critical path list for workflow A is A1→A2→A3→A5→A4 and the critical path list for workflow B is B1→B3→B4→B5→B2. A1, A2, B1 and B3 have been finished. A3, A4, B2 and B4 are ready. A5 and B5 are unready. According to the order in the critical path lists, ***CPWS*** submits A3 and B4 tasks.

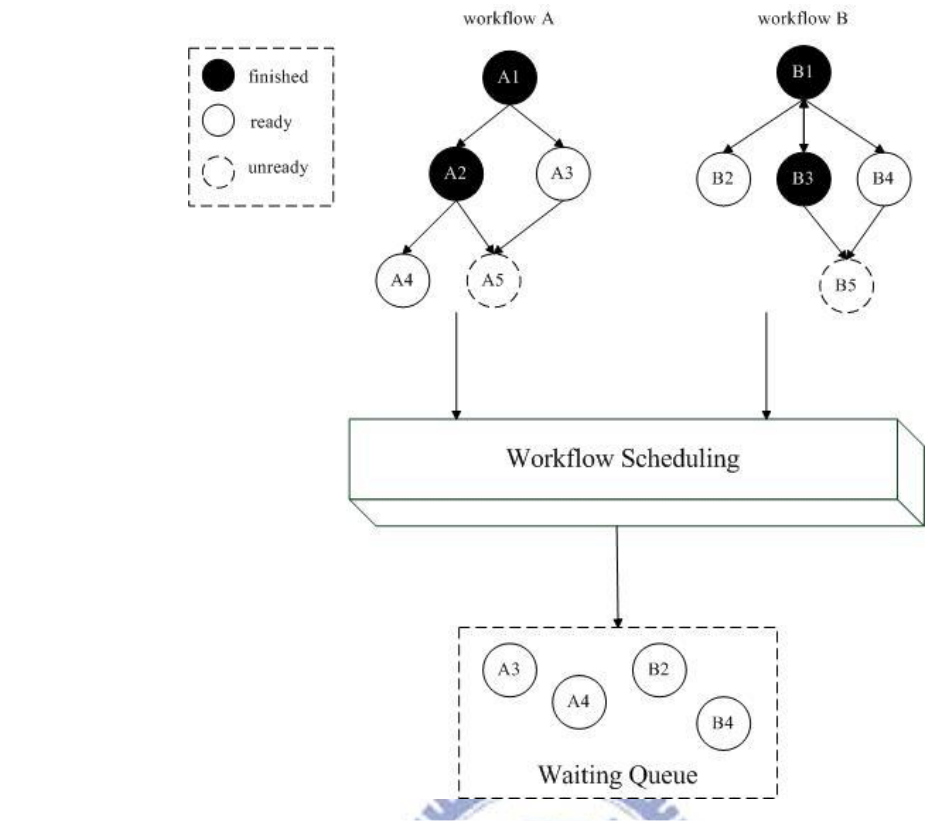


Figure 4-2 An example of ***SWS***

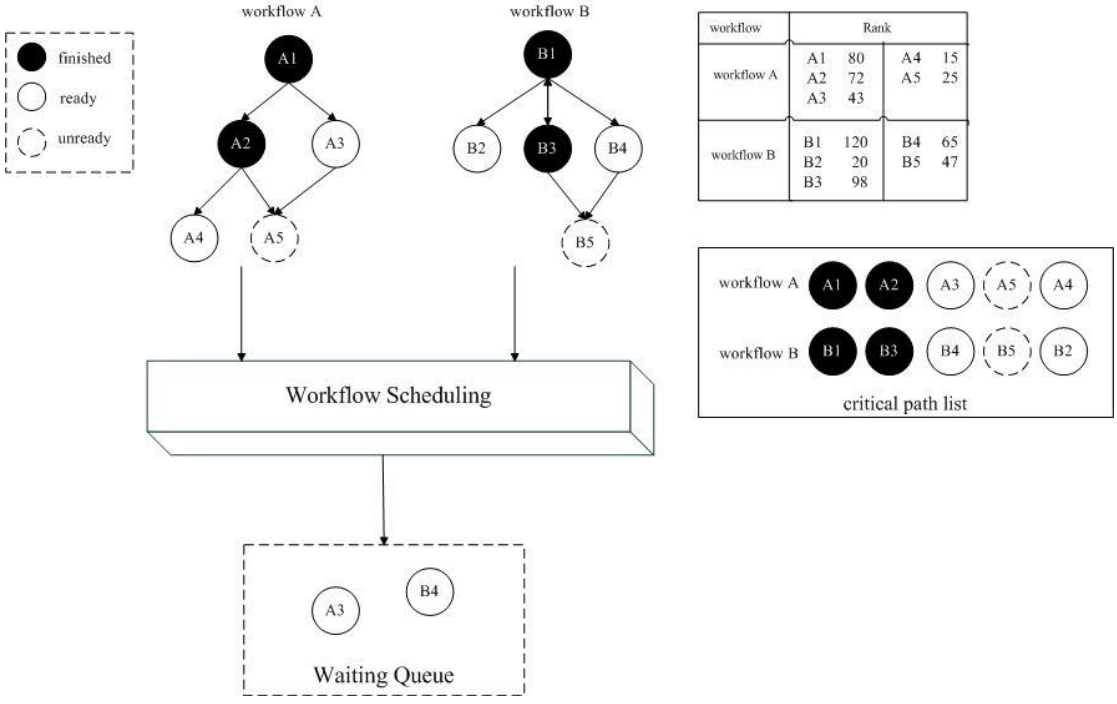


Figure 4-3 An example of ***CPWS***

4.2.3 Adaptive Allocation (AA)

To improve the precision, we define the following quantities:

- The **Estimated Computation Time ECT(*t, p*)** is defined as the estimated execution time of task *t* on processor group *p*.
- The **Estimated File Communication Time EFCT(*t, p*)** is defined as the estimated communication time required by task *t* on processor group *p* to receive all necessary files before execution.
- The **Estimated Available Time EAT(*t, p*)** is defined as the earliest time when processor group *p* has a large enough time slot to execute task *t*.
- The **Estimated Finish Time EFT(*t, p*)** is defined as the estimated time when task *t* completes on processor group *p*:

$$EFT(t,p) = EAT(t,p) + ECT(t,p) + EFCT(t,p)$$

The task allocation method in RANK_HYBD [21] selects the highest priority task and allocates it to the free processor group that has the earliest estimated finish time. We call this approach as ***Simple Allocation*** (***SA***). In this thesis, we propose a new approach called ***Adaptive Allocation*** (***AA***). The main idea of ***AA*** is described below:

1. When the number of clusters that can accommodate the first task is 1, it finds the processor group with the earliest estimated available time among other clusters. If the estimated finish time of the first task on that processor group in the future is earlier than that on the free processor group, the task will be kept in the waiting queue. Otherwise, the system allocates the task to the free processor group right away.
2. When the number of clusters that can accommodate the highest priority task is larger than 1, it allocates the highest priority task to the free processor group that has the earliest estimated finish time.

AA is described in Algorithm 4-2 which indicates a loop. When there are free processors and the waiting queue contains at least one task, it selects the first tasks and follows above allocation rules. In parallel task scheduling, if the number of free processors is not enough for a task, the idle processors become a scheduling hole. To overcome this problem, we import multi-processor task rearrangement, i.e., first fit, easy backfilling [22] or conservative backfilling [22] to fix the scheduling hole as shown in lines 4 to 5. First fit approach finds the first waiting task that can be moved to fix the scheduling hole. Conservative backfilling approach moves tasks forward only if they do not delay previously queued task. Easy backfilling approach is more aggressive and allows tasks to skip ahead provided they do not delay the job at the head of the queue [22]. Lines 25 to 31 show that a function (*allocateNumberOfClusters*(R, t_i)). It returns the number of clusters that can accommodate the first task. If the function returns 1, the steps in lines 8 to 16 work for item 1 described previously. If the function returns a number larger than 1, the steps in lines 17 to 22 work for item 2.

T: a set of tasks in the waiting queue
R: a set of free processors
C: a set of clusters

AA(T,R,C)
01 **begin**
02 **while**($T \neq \emptyset \; and \; R \neq \emptyset$) **do**
03 select $t_i \in T$, where t_i with the highest priority task;
04 **If** workflows are composed of data-parallel tasks
05 ***Multi-Processor Task Rearrangement;

06 **If** *allocateNumberOfClusters*(R, t_i) = 0
07 task t_i keeps waiting in the waiting queue;
08 **else if** *allocateNumberOfClusters*(R, t_i) = 1
09 the free processor group $p_x \in C_x$ and calculate $EFT(t_i, p_x)$;
10 find the processor group $p_y \in C_y$ with the earliest estimated available time among other clusters, where $C_x \neq C_y$;
11 **If** $EFT(t_i, p_x) \leq EFT(t_i, p_y)$
12 Assign task t_i to the processor(s) p_x;
13 $T = T - \{t_i\}$;
14 $R = R - \{p_x\}$;
15 **else**
16 task t_i keeps waiting in the waiting queue;
17 **else** // *allocateNumberOfClusters*(R, t_i)> 1
18 **for** each processor group $p_k \in R$ **do**
19 calculate $EFT(t_i, p_k)$; // EAT(t_i,p_k) = current time
20 Assign task t_i to the processor group p_k that has earliest estimated finish time, $EFT(t_i, p_k)$;
21 $T = T - \{t_i\}$;
22 $R = R - \{p_k\}$;
23 **end while**
24 **end**

```
25      int allocateNumberOfClusters(R, t_i){
26          numberOfCluster=0;
27          for each cluster C_i do
28              If free processors in C_i ≥ processors that t_i requires
29                  numberOfClusters++;
30          return numberOfClusters;
31      }
```

*Each simulation selects one of first fit, easy backfilling and conservative backfilling approaches;

Algorithm 4-2. AA algorithm

Chapter 5 Experimental Results

This chapter presents the experimental results of the proposed method. Section 5.1 introduces the performance metrics used. Section 5.2 describes experimental results for workflows composed of single-processor tasks. Section 5.3 presents experimental results for workflows composed of data-parallel tasks.

5.1 Performance Metrics

The performance metrics used in our experiments are described below:

- **makespan**: the time between submission and completion of a workflow, including execution time and waiting time.
- **Schedule Length Ratio** (**SLR**): makespan usually varies widely among workflows with different sizes and other properties. To measure the scheduling efficiency objectively, we can use another performance metric derived from makespan, which calculates the ratio of a workflow's makespan over the best possible schedule length in a given environment. The performance is called Schedule Length Ratio (SLR) and defined by

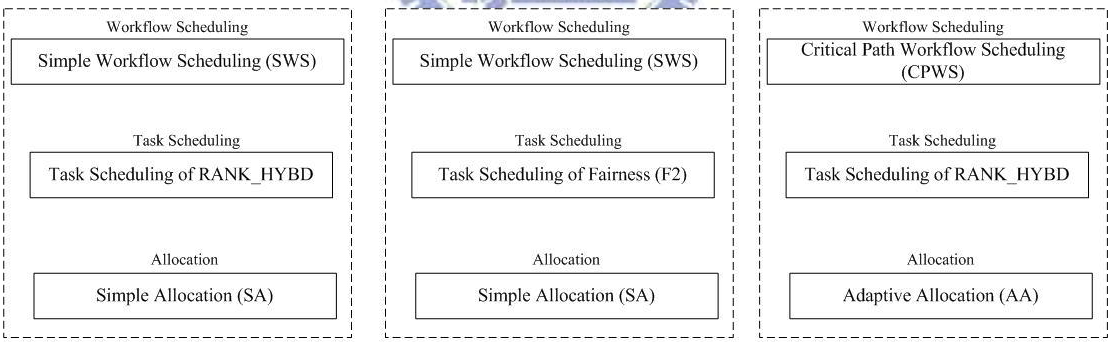
  $$SLR = \frac{makespan}{CPL}$$

  , where CPL represents the Critical Path Length of a workflow. SLR is not sensitive to the size of a workflow.
- **win** (**%**): used for the comparison of different algorithms. For a workflow, one of the algorithms has shortest makespan. The win value of an algorithm means the percentage of the workflows that have the shortest makespan. From users' perspective, the higher win value leads to the higher satisfaction.

5.2 Experimental Results for Workflows Composed of Single-Processor Tasks

5.2.1 Difference between RANK_HYBD, Fairness_Dynamic and OWM

We partition the complete scheduling process into three components, workflow scheduling, task scheduling and allocation approaches, for clearly clarifying the differences among different scheduling approaches. Z Yu et al. [21] propose a dynamic algorithm for online workflows, ***RANK_HYBD*** as shown in figure 5-1(a). The original Fairness approach (F2) in [20] is a static algorithm and can not deal with online workflows. In the following experiments, we modify the Fairness (F2) approach to handle online workflows by replacing the original workflow scheduling and allocation approaches in this approach with ***SWS*** and ***SA*** respectively. We call this new approach as ***Fairness_Dynamic*** in figure 5-1.



(a) RANK_HYBD (b) Fairness_Dynamic (c) OWM

Figure 5-1 The difference between RANK_HYBD, Fairness_Dynamic and OWM

5.2.2 Experimental Setup

To experiment with different workload characteristics, we use the following parameters to generate different types of workflows. A workflow is represented as a Directed Acyclic Graph (DAG).

- Node={20, 40, 60, 80, 100}
- Shape={0.5, 1.0, 2.0}
- OutDegree={1, 2, 3, 4, 5}
- CCR={0.1, 0.5, 1.0, 1.5, 2.0}
- BRange={0.1, 0.25, 0.5, 0.75, 1.0}
- WDAG=100~1000

The values of these parameters are randomly selected from the corresponding sets given above for each DAG. The arrival interval value between DAGs is set based on Poisson distribution. Each experiment involves 20 runs, and each run has 100 unique DAGs on a Grid environment that contains 3 clusters each containing 30~50 processors respectively.

In the experiment, we also take other factors into account: the distribution of tasks' computation cost (*Wi_DisType*) and the computation intensity of a workflow represented by CCR (*computationIntensity*). The average computation cost of each task is randomly generated from a probability distribution within the range $[1, 2 \times \text{WDAG}]$ as described in Chapter 3. We experimented with both a uniform distribution and an exponential distribution for tasks' computation cost. For the computation intensity of a workflow, we refer a workflow to computation intensive if its computation time is longer than file communication time. Otherwise, a workflow is communication intensive. For general workflows, CCR is randomly selected from the set {0.1, 0.5, 1.0, 1.5, 2.0}. For computation-intensive workflows, CCR is randomly selected form the set {0.1, 0.5}, and for communication-intensive workflows, CCR is

randomly selected from the set {1.5, 2.0}.

5.2.3 Results Analyses

A. Impact of the Arrival Interval of workflows

Figure 5-2, 5-3 and 5-4 show the results of different mean arrival intervals for average makespan, average SLR and win (%) respectively. It can be easily seen that when the system is more crowded, i.e., smaller arrival interval in the figures, ***OWM*** outperforms the other two algorithms significantly. When all DAGs are submitted at the same time, i.e., the zero arrival interval in the figures, ***OWM*** outperforms ***Fainess_Dynamic*** by 26% and 49%, and outperforms ***RANK_HYBD*** by 13% and 20% for average makespan and average SLR respectively, as shown in figure 5-2 and 5-3. ***Fairness_Dynamic*** has pool performance for average SLR, because it achieves fairness by the cost of enlarging the makespan of the workflows with shorter critical path length. ***OWM*** wins in terms of makespan by 94.55% as shown in figure 5-4. From users' perspective, it means 94.55% users may prefer ***OWM***. When workflows arrive at an interval about 400 time units, these three algorithms are almost equivalent for average makespan, average SLR and win (%) because one workflow almost come in after another one finishes. In real environments, most high-performance centers are overloaded, therefore ***OWM*** can outperform others in such environments.

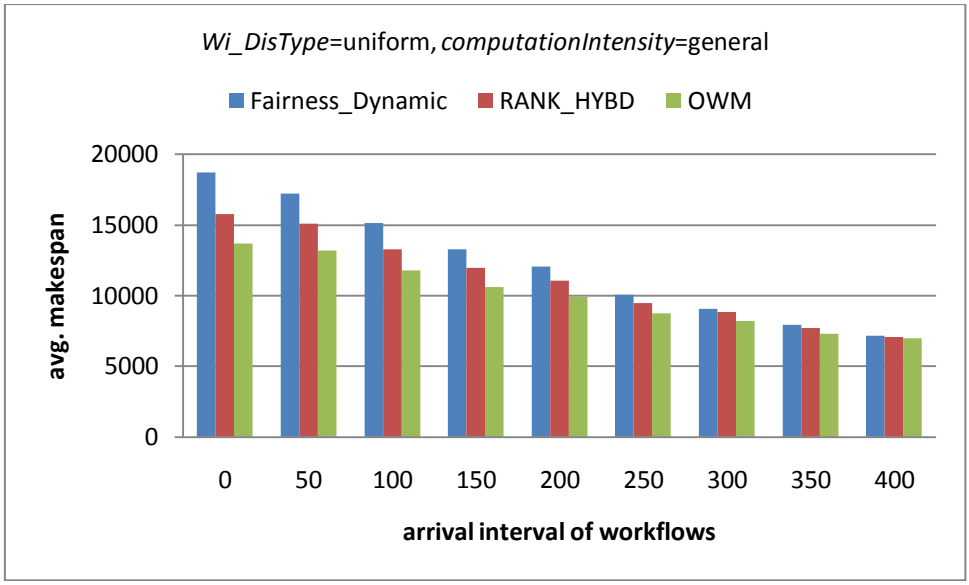


Figure 5-2 Results of different mean arrival intervals for average makespan

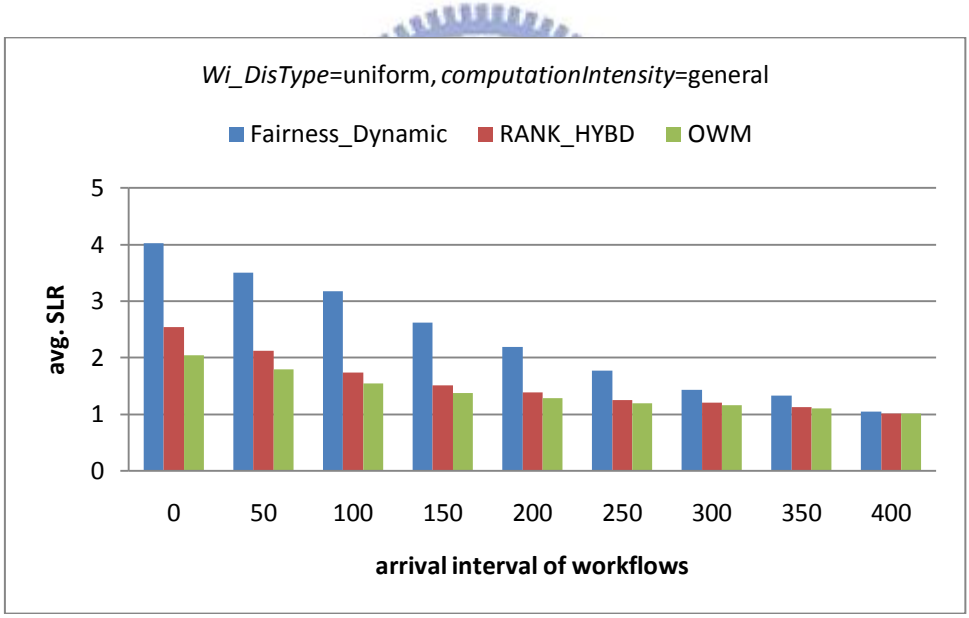


Figure 5-3 Results of different mean arrival intervals for average SLR

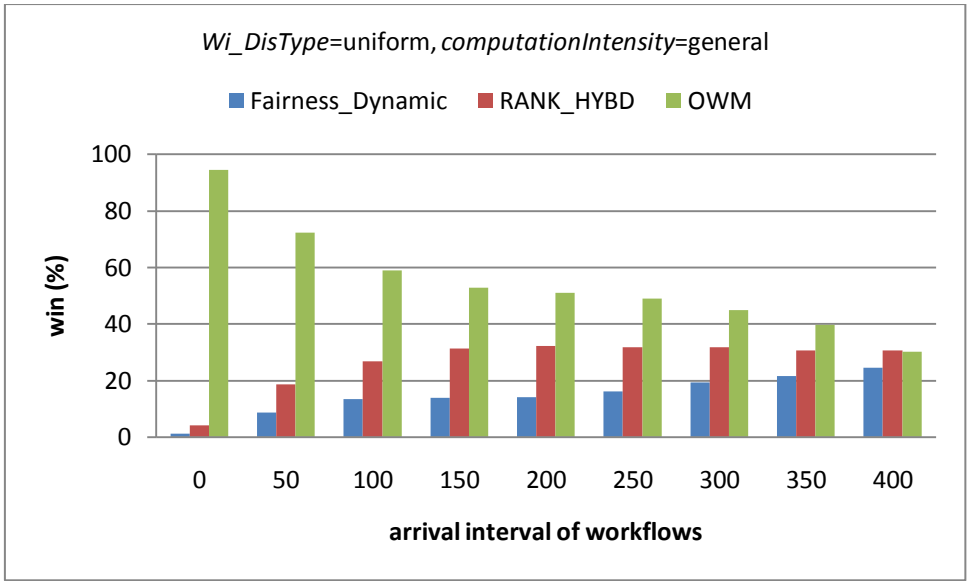


Figure 5-4 Results of different mean arrival intervals for win (%)

B. Impact of the Computation Intensity with Different Distributions of Tasks' Computation Cost

Figure 5-5, 5-6 and 5-7 show the results of computation intensity at different levels for average makespan, average SLR and win (%) with a uniform distribution of tasks' computation cost respectively. Figure 5-8, 5-9 and 5-10 show the results with an exponential distribution of tasks' computation cost. In these experiments, the arrival interval of workflows is set with the Poisson distribution with the mean value of 20. It represents a global level that several workflows may be simultaneously running in the system. Obviously, ***OWM*** outperforms the other two algorithms. The superiority of ***OWM*** over the other two methods is that it consistently achieves the best performance for all types of workflows.

In figure 5-5, ***OWM*** outperforms ***Fairness_Dynamic*** by 23%, 22% and 27%, and outperforms ***RANK_HYBD*** by 12%, 17% and 11% in terms of average makespan for general, computation and communication intensive workflows respectively. In

figure 5-6, ***OWM*** outperforms ***Fairness_Dynamic*** by 44%, 45% and 45%, and outperforms ***RANK_HYBD*** by 16%, 19% and 14% in terms of SLR for general, computation and communication intensive workflows respectively. ***OWM*** wins in terms of makespan by about 82% for all the three types of workflows as show in figure 5-7.

In figure 5-8, OWM outperforms Fairness_Dynamic by 17%, 14% and 20%, and outperforms RANK_HYBD by 16%, 20% and 15% in terms of average makespan for general, computation and communication intensive workflows respectively. In figure 5-9, ***OWM*** outperforms ***Fairness_Dynamic*** by 24%, 20% and 26%, and outperforms ***RANK_HYBD*** by 20%, 23% and 18% for in terms of average SLR for general, computation and communication intensive workflows respectively. ***OWM*** wins in terms of makespan by about 72% for all the three types of workflows as show in figure 5-10.

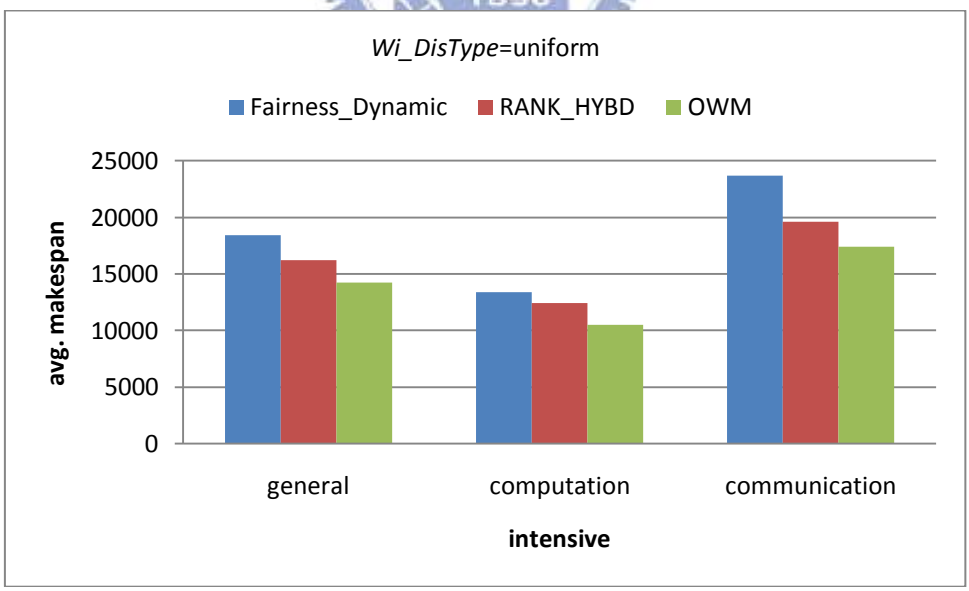


Figure 5-5 Results of different computation intensity for average makespan with a uniform distribution of tasks' computation cost

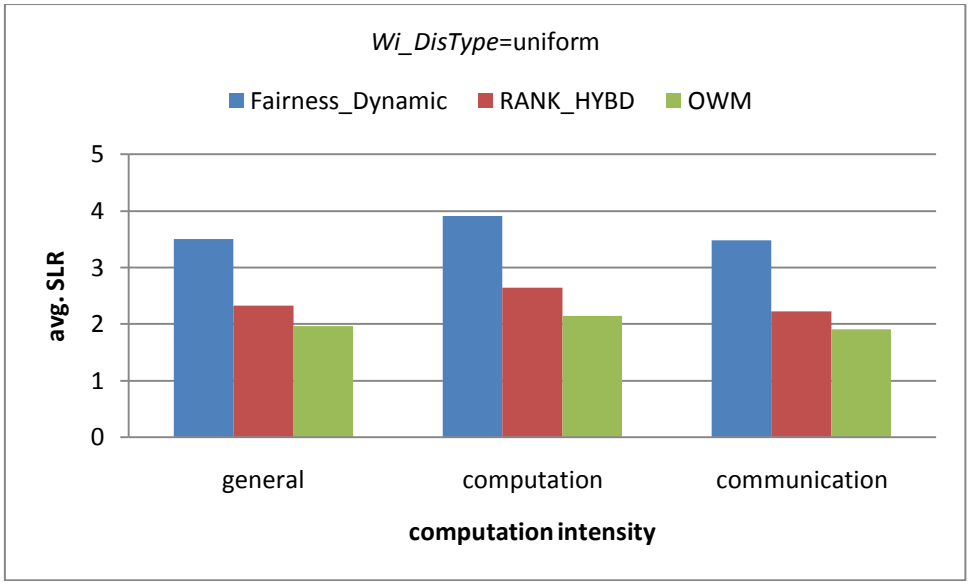


Figure 5-6 Results of different computation intensity for average SLR with a uniform distribution of tasks' computation cost

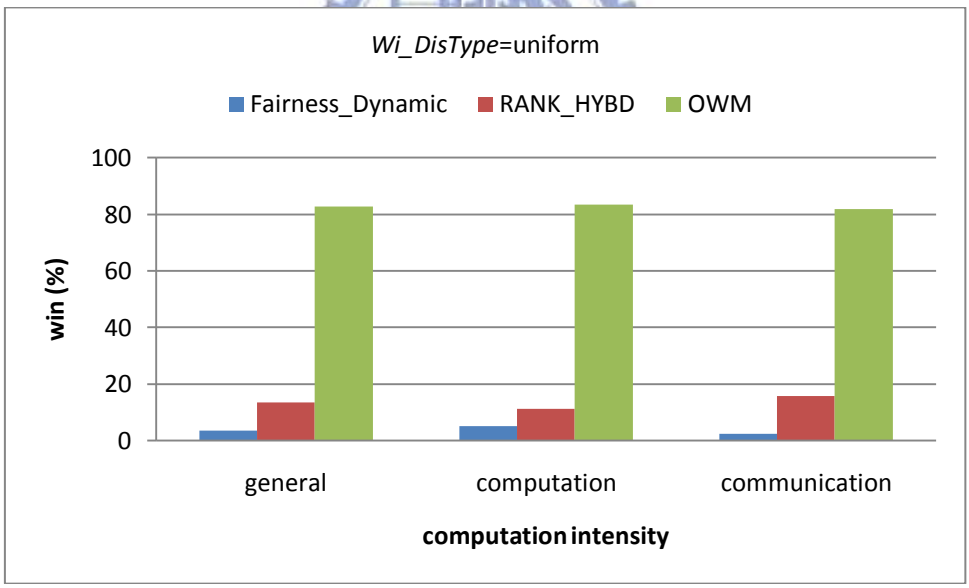


Figure 5-7 Results of different computation intensity for win (%) with a uniform distribution of tasks' computation cost

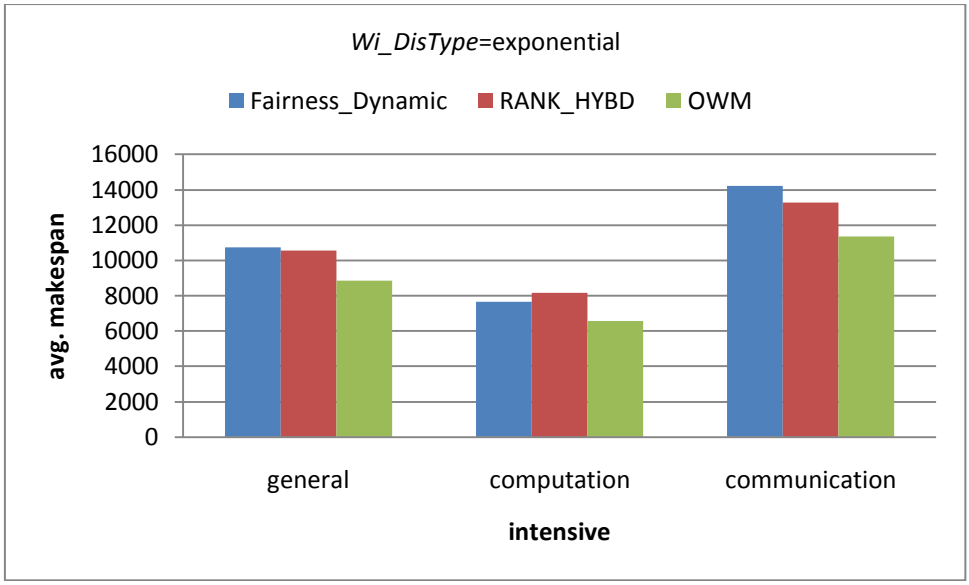


Figure 5-8 Results of different computation intensity for average makespan with an exponential distribution of tasks' computation cost

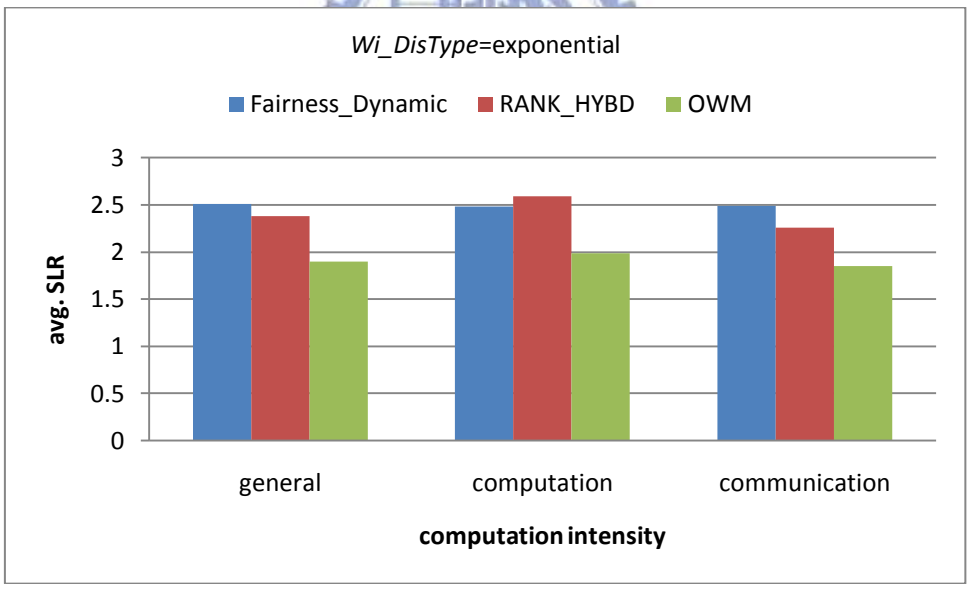


Figure 5-9 Results of different computation intensity for average SLR with an exponential distribution of tasks' computation cost

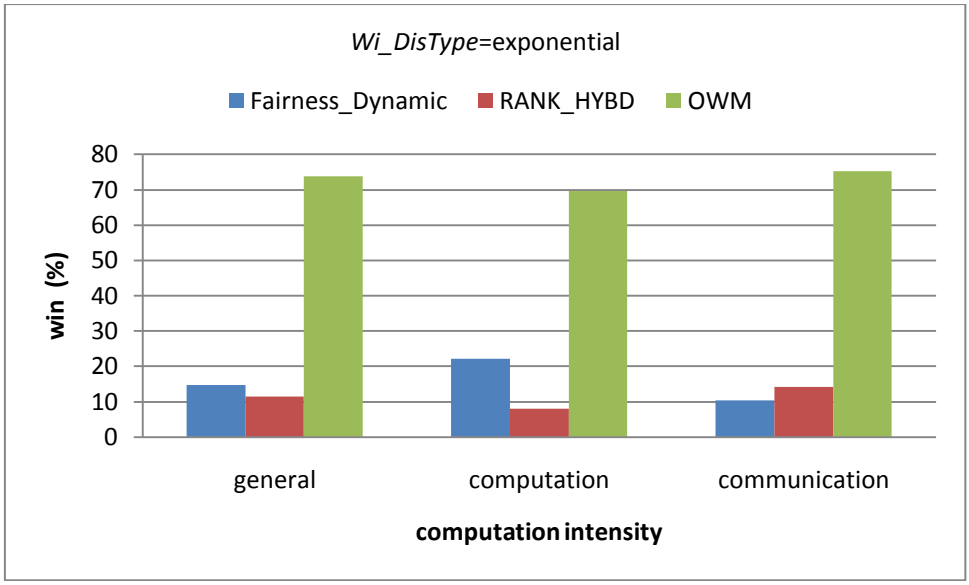


Figure 5-10 Results of different computation intensity for win (%) with an exponential distribution of tasks' computation cost

C. Impact of the Number of Clusters

The following investigate the effects of cluster amount in a Grid environment. In the experiment, the Grid environment is composed of 120 processors, and divided equally into a different number of clusters, 2, 4, 6, 8, 10 and 12, for each test case. We assume the arrival interval of workflows conforms to the Poisson distribution with the mean value of 20. The results indicate that in average, ***OWM*** outperforms ***Fairness_Dynamic*** by 22%, and outperforms ***RANK_HYBD*** by 11% in terms of average makespan as shown in figure 5-1l. ***OWM*** outperforms ***Fairness_Dynamic*** by 48%, and outperforms ***RANK_HYBD*** by 15% in terms of average SLR as shown in figure 5-12. ***OWM*** wins in terms of makespan by about 82% as shown in figure 5-13.

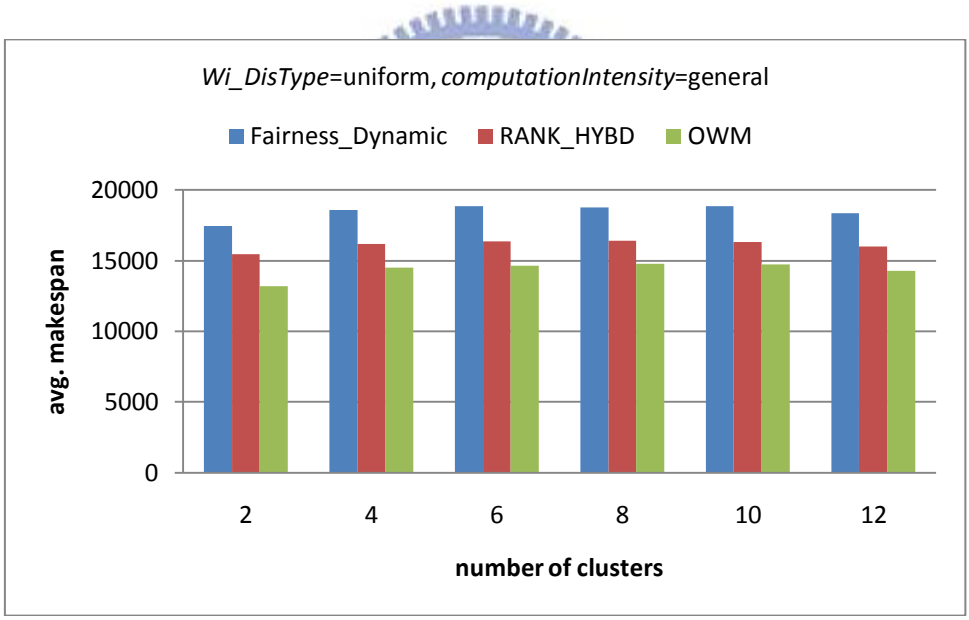


Figure 5-11 Results of different number of clusters for average makespan

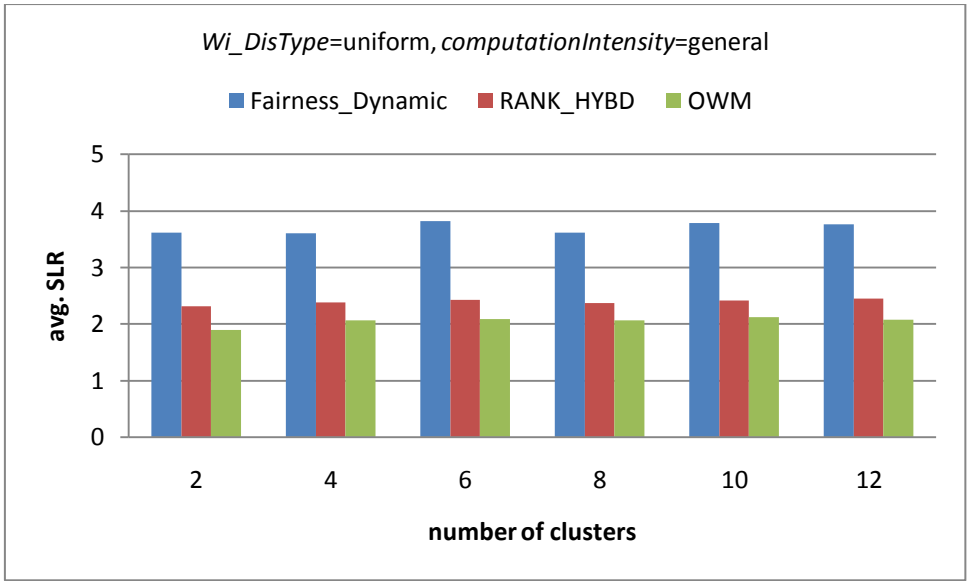


Figure 5-12 Results of different number of clusters for average SLR

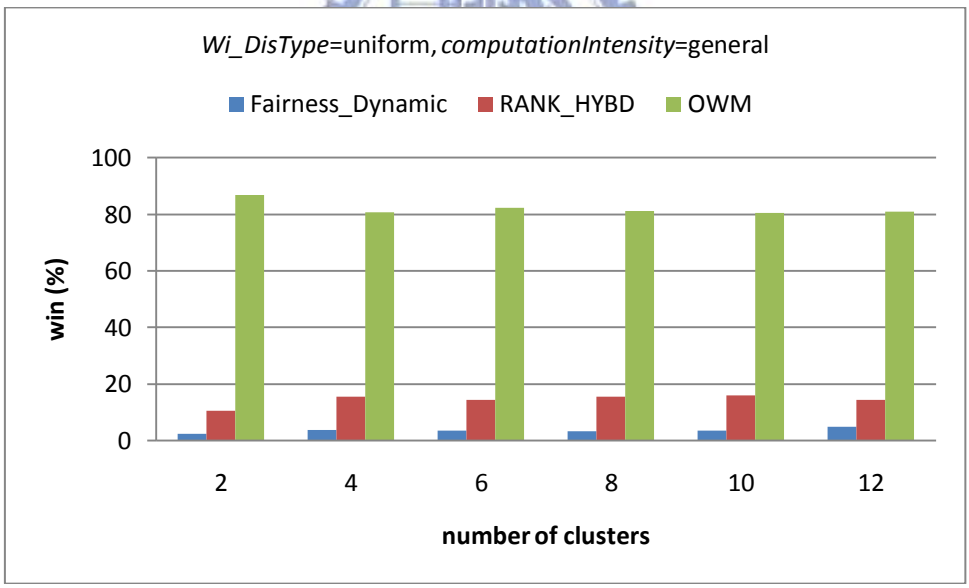


Figure 5-13 Results of different number of clusters for win (%)

D. Impact of Inaccurate Execution Estimates

The execution time of each task on a specific processor is necessary information for workflow scheduling algorithms. In practice, the execution time of a task is usually difficult to known before the execution completes. Therefore, the execution time used in scheduling algorithm s is not precise. The following experiments investigate the effects of inaccurate estimation of task execution time. The simulator picks the actual execution time of a task randomly from the range:

$$[1, \left(et + 2 \times \frac{uncertainty}{100} \times et\right)]$$

, where et is the estimated execution time of the task. For example, when the uncertainty is 400 and et of a task is 100, the actual execution time of the task is randomly picked from the range: [1, 900]. We also assume that the arrival interval of workflows conforms to the Poisson distribution with the mean value of 20. Figure 5-14, 5-15 and 5-16 show the results of inaccurate execution estimates for average makespan, average SLR and win (%) respectively. It can be easily observed that ***OWM*** outperforms the other two algorithms for the uncertainty levels from 50% to 400%. In average, ***OWM*** outperforms ***Fairness_Dynamic*** by 19%, and outperforms ***RANK_HYBD*** by 8% for average makespan as shown in figure 5-14; ***OWM*** outperforms ***Fairness_Dynamic*** by 38%, and outperforms ***RANK_HYBD*** by 12% for average SLR as shown in figure 5-15. ***OWM*** wins in terms of makespan by about 74% as shown in figure 5-16. These results indicate that ***OWM*** is more resilient to inaccurate estimation of task execution time than the other methods.

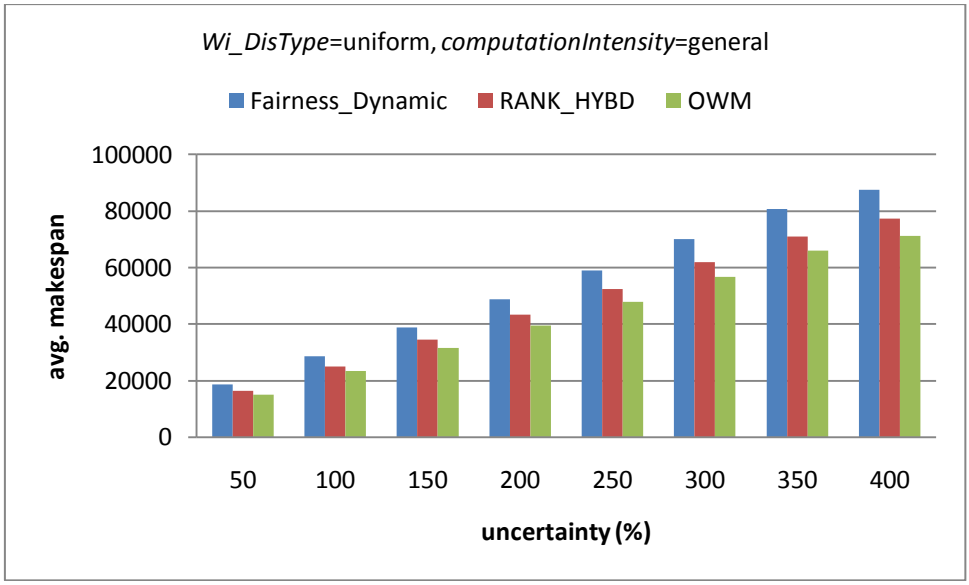


Figure 5-14 Results of inaccurate execution estimates for average makespan

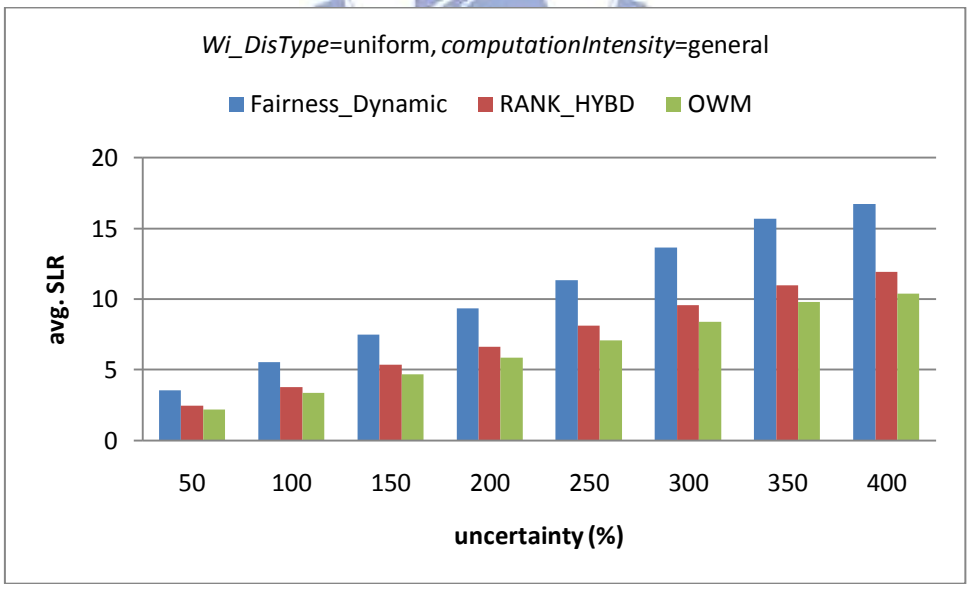


Figure 5-15 Results of inaccurate execution estimates for average SLR

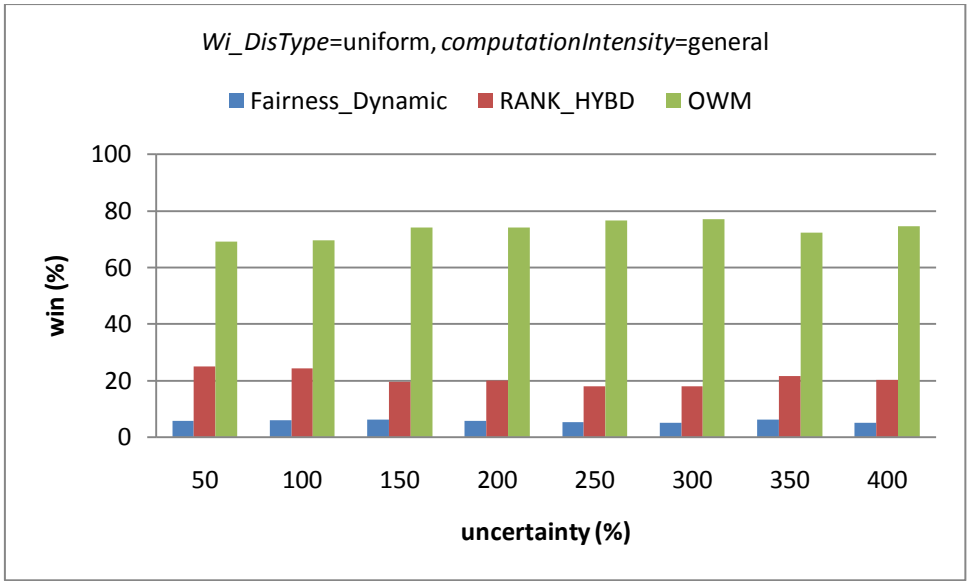


Figure 5-16 Results of inaccurate execution estimates for win (%)

5.3 Experimental Results for Workflows Composed of Data-Parallel Tasks

In this section, we compare different multi-processor task rearrangement processes including first fit, easy backfilling [22] and conservative backfilling [22] approaches with FCFS (First Come First Serve) approach. The FCFS approach doesn't find waiting task to fit the scheduling hole. In the experiments, ***OWM(FCFS)***, ***OWM(conservative)***, ***OWM(easy)*** and ***OWM(first fit)*** stand for FCFS, conservative backfilling, easy backfilling and first fit approaches respectively. Figure 5-17 shows the main processes in ***OWM(FCFS)***, ***OWM(conservative)***, ***OWM(easy)*** and ***OWM(first fit)***.

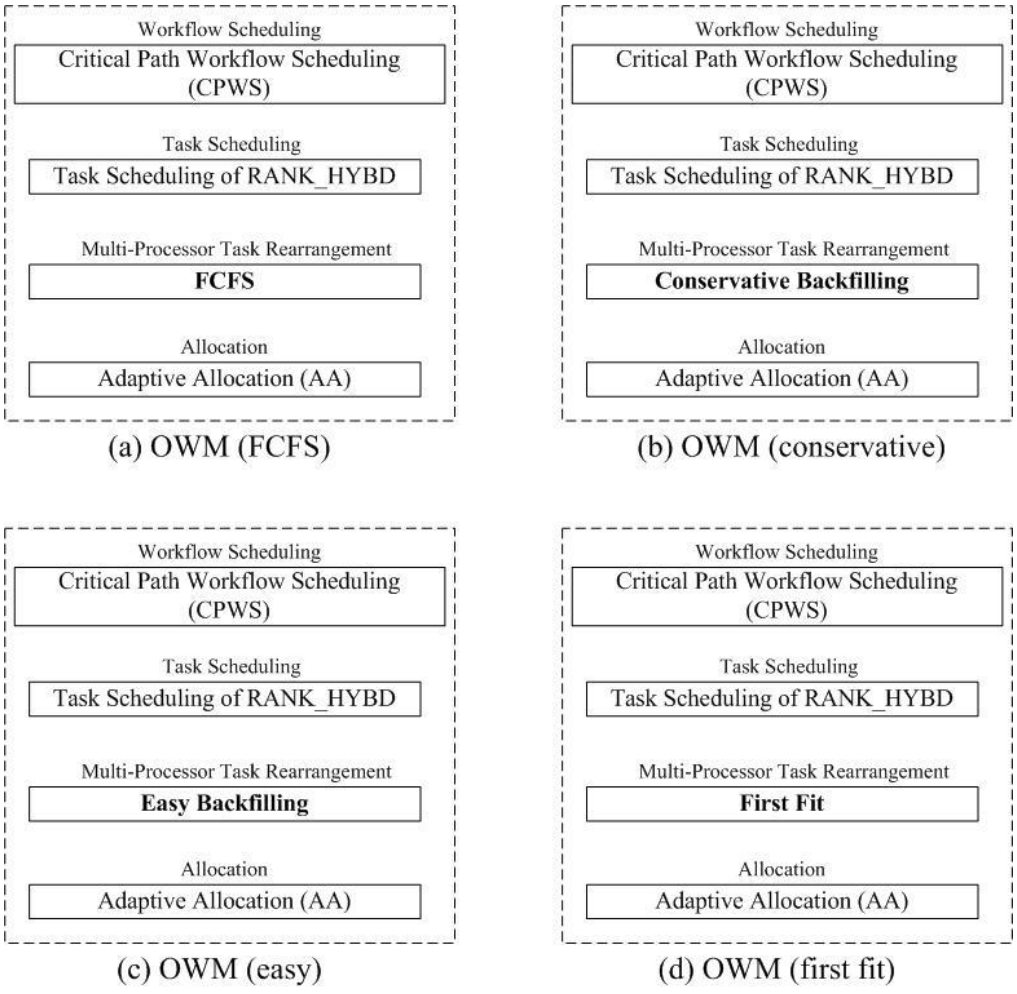


Figure 5-17 The processes in OWM(FCFS), OWM(conservative), OWM(easy) and OWM(first fit)

5.3.1 Experimental Setup

The experimental setups for data-parallel tasks are the same as that for single-processor tasks, but each run has 50 unique workflows. To be more realistic, maximal required processors of all tasks (*maxTaskNP*) and the distribution of the processors that tasks require (*NP_DisType*) are taken into account. In the experiment, *maxTaskNP* is defined with maximum, half and minimum.

- *maxTaskNP* is maximum: *maxTaskNP* = the number of processors in the smallest cluster in the Grid environment.
- *maxTaskNP* is half: *maxTaskNP* = $\frac{1}{2}\times$the number of processors in the smallest cluster in the Grid environment.
- *maxTaskNP* is minimum: *maxTaskNP* = $\frac{1}{5}\times$the number of processors in the smallest cluster in the Grid environment.

The required processors of each task is randomly generated from a probability distribution within the range $[1, maxTaskNP]$. The experiment is done with uniform distribution, exponential distribution and normal distribution for *NP_DisType*.

5.3.2 Results Analyses

Each experiment is configured by the following four parameters. Their values are assigned from the corresponding sets below:

- *Wi_DisType*={uniform, exponential}
- *maxTaskNP*={maximum, half, minimum}
- *NP_DisType*={uniform, exponential, normal}
- *computationIntensity*={general, computation, communication}

The combinations of the above parameter values give 54 different experiments. These 54 experiments lead to an interesting observation for workflow scheduling. In independent task scheduling, it is well known that FCFS approach has worse performance than conservative backfilling [22], easy backfilling and first fit approaches. However, in workflow scheduling, the experiments show that ***OWM(FCFS)*** is almost equal to ***OWM(conservative)***, and outperforms ***OWM(easy)*** and ***OWM(first fit)*** for average SLR, and outperforms the other three approaches for win (%). The results indicate that that when the waiting tasks are rearranged by the multi-processor task rearrangement process, it doesn't result in better performance as expected. The following example helps to explain the reason. The tasks in the waiting queue are sorted by their critical path in the ascending order. Suppose that a workflow is near completion, and the last task in the workflow will get the highest priority in the waiting queue. If the task cannot be allocated due to the lack of free processors, the multi-processor task rearrangement process will find a waiting task to fit the scheduling hole. The above rearrangement technique may make the last task to wait infinitely, and it in turn increases the makespan of the workflow. So, the performance may be reduced correspondingly. Therefore, frequent the task rearrangement may contrarily lead to poor performance. For example, ***OWM(first fit)*** has the highest frequency of task rearrangement, and may result in the worst performance.

Figure 5-18, 5-19 and 5-20 are an example among the 54 experiments. Other experimental results are shown in Appendix. Figure 5-18, 5-19 and 5-20 show the results of different computation intensity for average makespan, average SLR and win (%) respectively, with *Wi_DisType*=uniform, *maxTaskNP*=min, and *NP_DisType*=uniform.

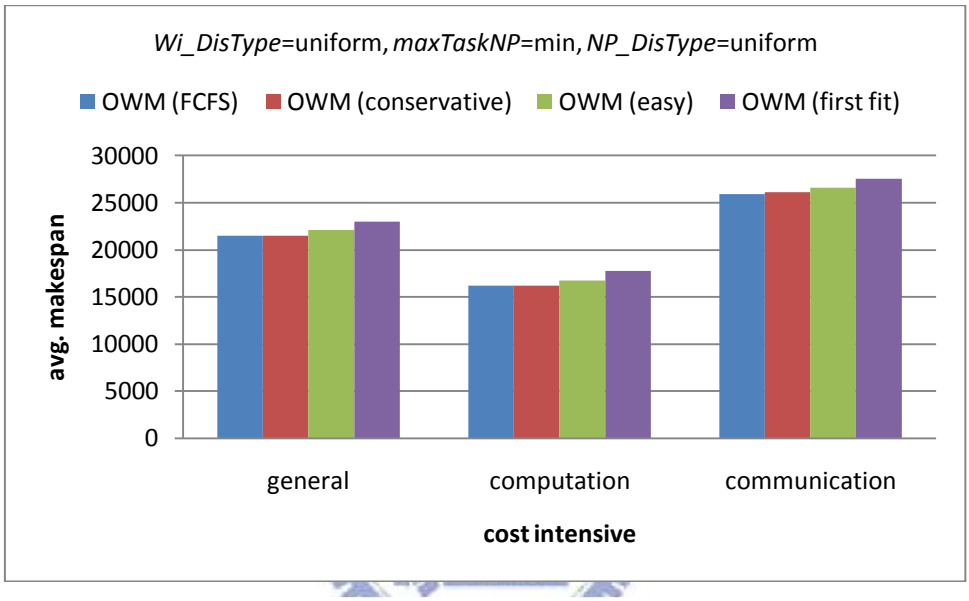


Figure 5-18 Results of different computation intensity for average makespan with (uniform, min, uniform)

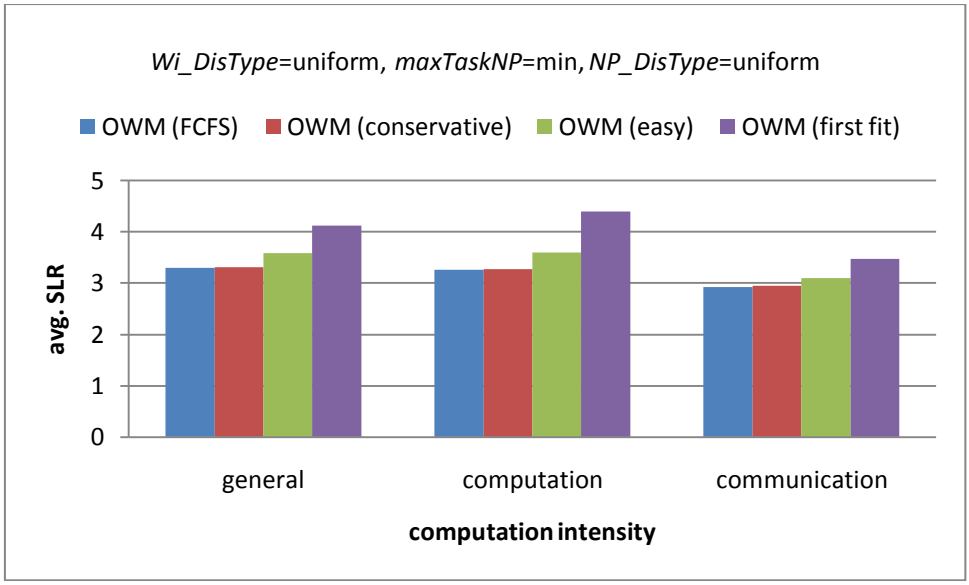


Figure 5-19 Results of different computation intensity for average SLR with (uniform, min, uniform)

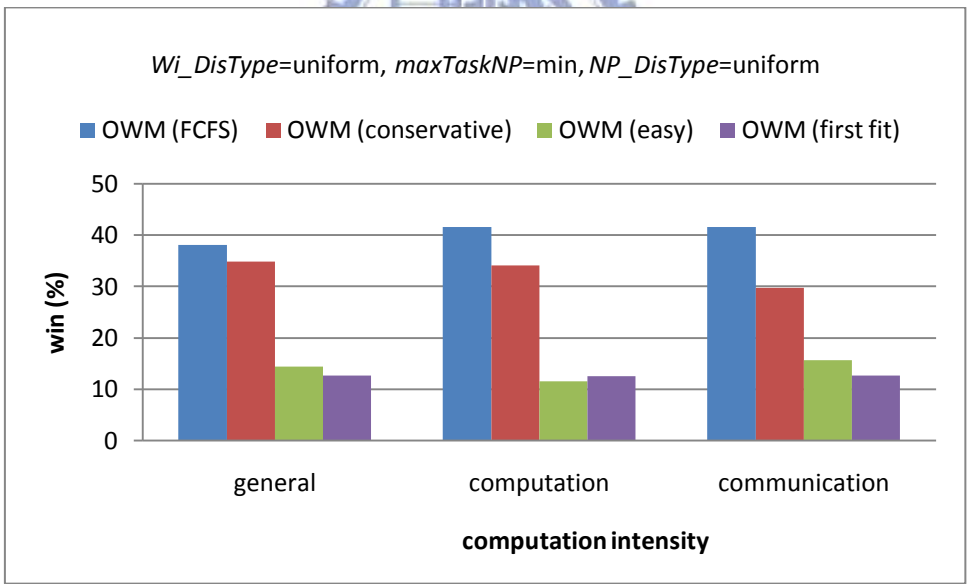


Figure 5-20 Results of different computation intensity for win (%) with (uniform, min, uniform)

Chapter 6 Conclusion and Future Work

Most workflow scheduling algorithms are restricted to the domain of single workflow. There are few researches for scheduling online workflows. In the thesis, we propose ***OWM*** approach for scheduling online workflows in a Grid environment. Our experiments show that ***OWM*** outperforms ***RANK_HYBD*** [21] and ***Fairness_Dynamic*** for average makesapn, average SLR and win (%) in different experimental workloads.

However, ***RANK_HYBD*** and ***Fairness_Dynamic*** do not work with workflows composed of data-parallel tasks. There are few studies focused on workflow scheduling for data-parallel tasks. The thesis takes this issue into account. We incorporate well-known approaches, e.g., first fit, easy backfilling [22] and conservative backfilling [22] into ***OWM*** to deal with workflows composed of data-parallel tasks. The experiments show that ***OWM(FCFS)*** is almost equal to ***OWM(conservative)***, and outperforms ***OWM(easy)*** and ***OWM(first fit)*** for average SLR, and outperforms the other three approaches for win (%).

In the future, we will investigate the trade-off between the QoS (Quality of Service) and the performance, i.e., the relation between the fairness and average makespan for workflows. In addition, we will implement ***OWM*** to real Grid environments to validate our simulation results.

Appendix

The remainder experimental results for workflows composed of data-parallel tasks are shown below.

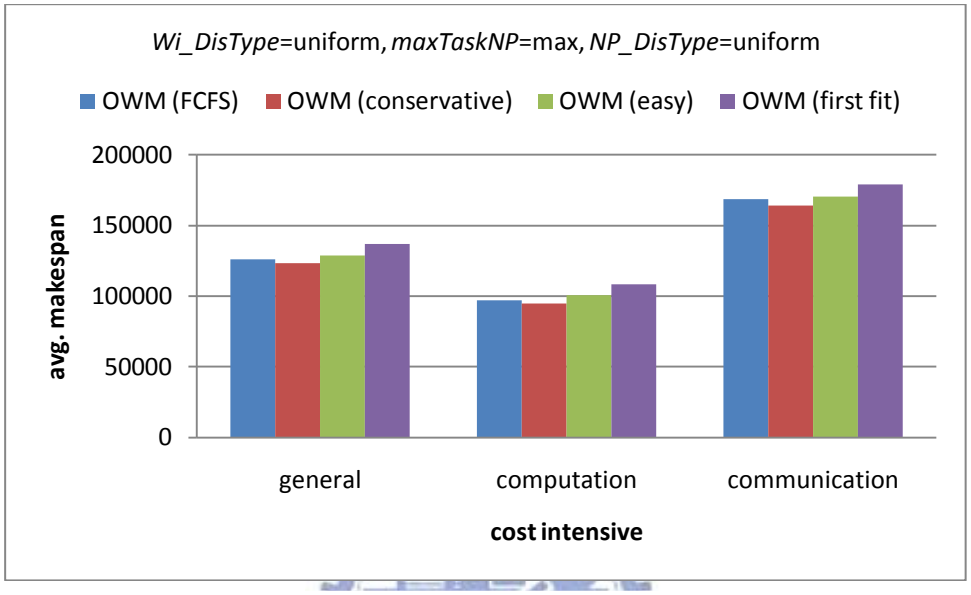


Figure A-1 Results of different computation intensity for average makespan with (uniform, max, uniform)

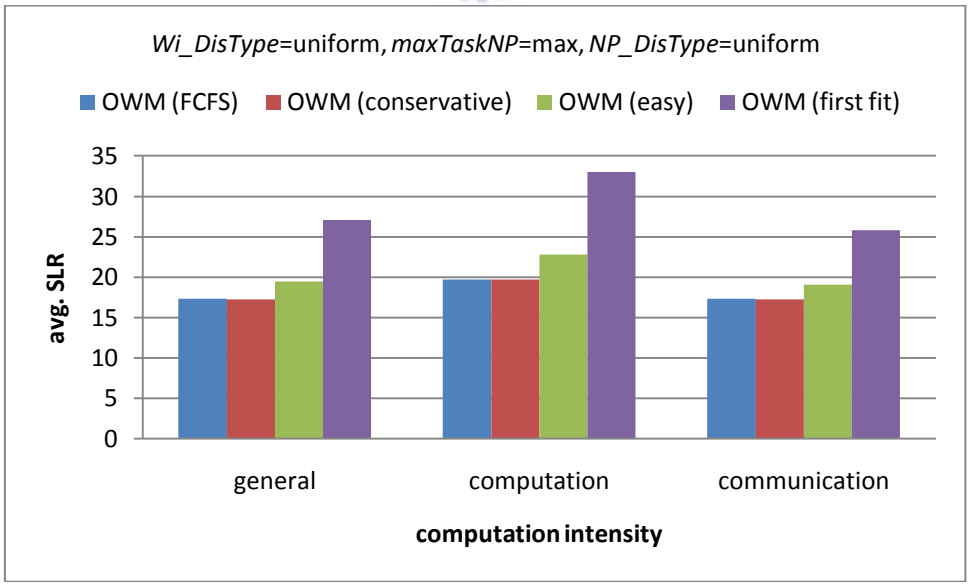


Figure A-2 Results of different computation intensity for average SLR with (uniform, max, uniform)

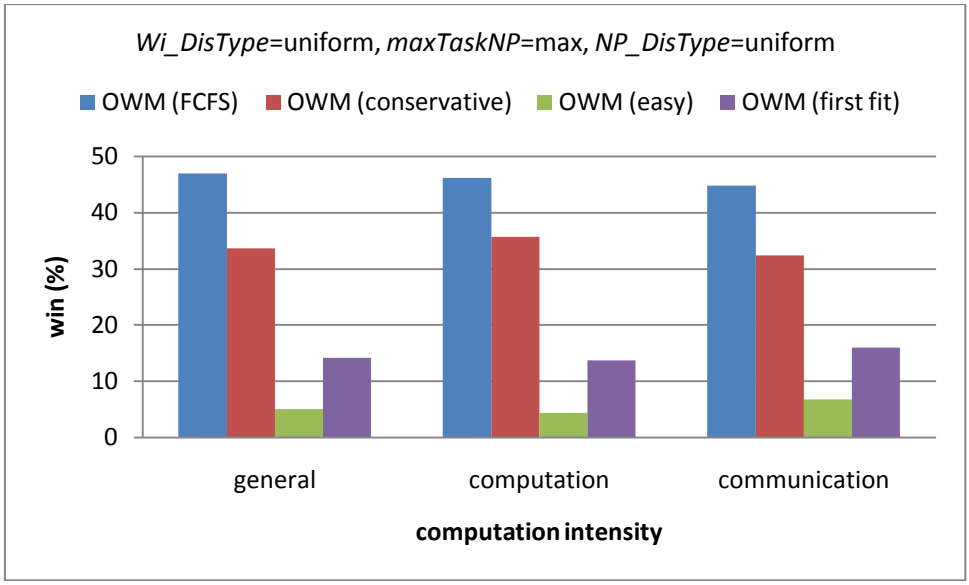


Figure A-3 Results of different computation intensity for win (%) with (uniform, max, uniform)

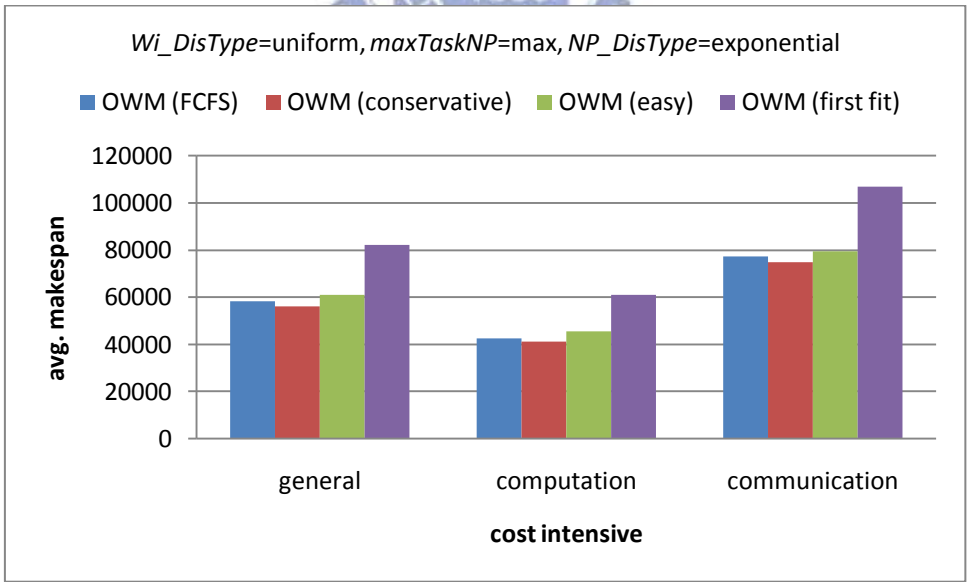


Figure A-4 Results of different computation intensity for average makespan with (uniform, max, exponential)

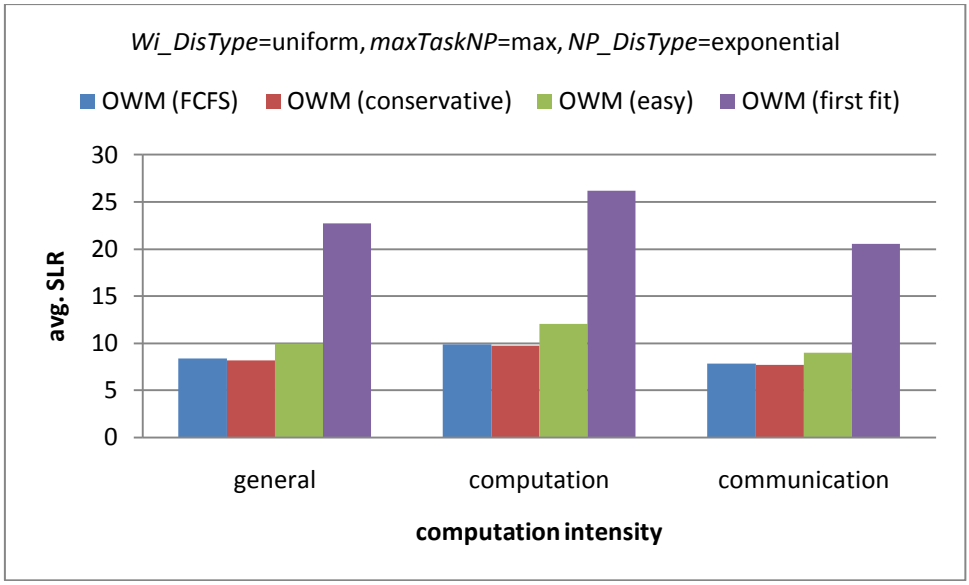


Figure A-5 Results of different computation intensity for average SLR with (uniform, max, exponential)

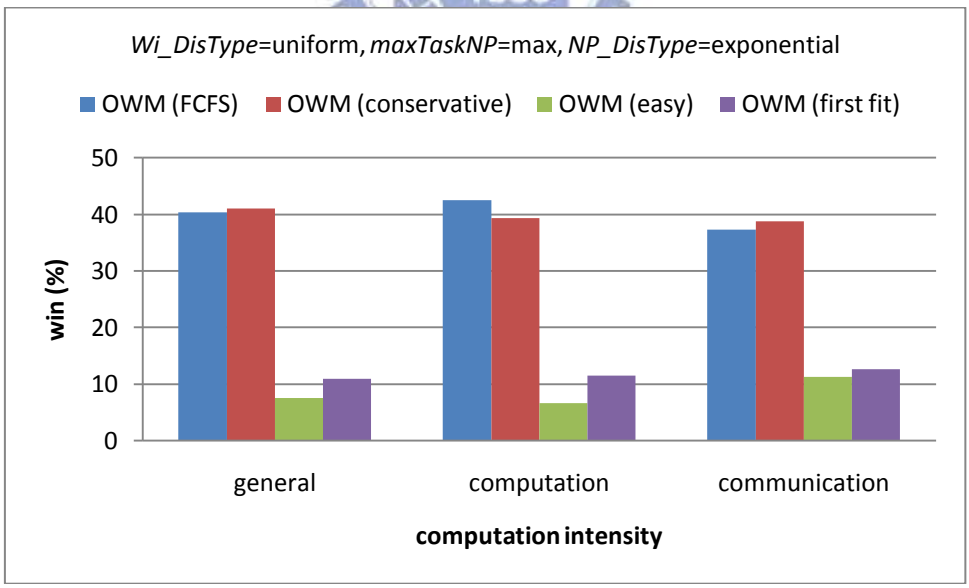


Figure A-6 Results of different computation intensity for win (%) with (uniform, max, exponential)

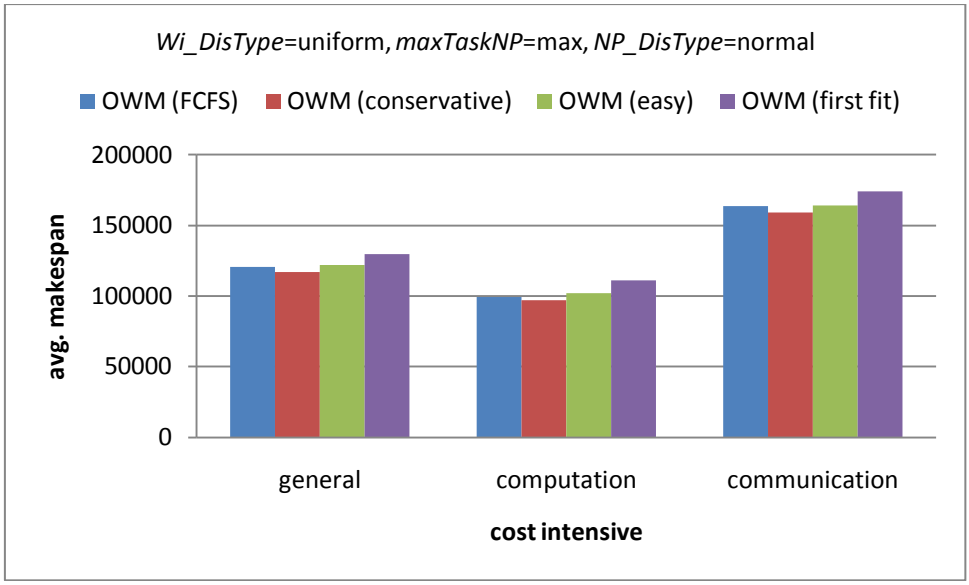


Figure A-7 Results of different computation intensity for average makespan with (uniform, max, normal)

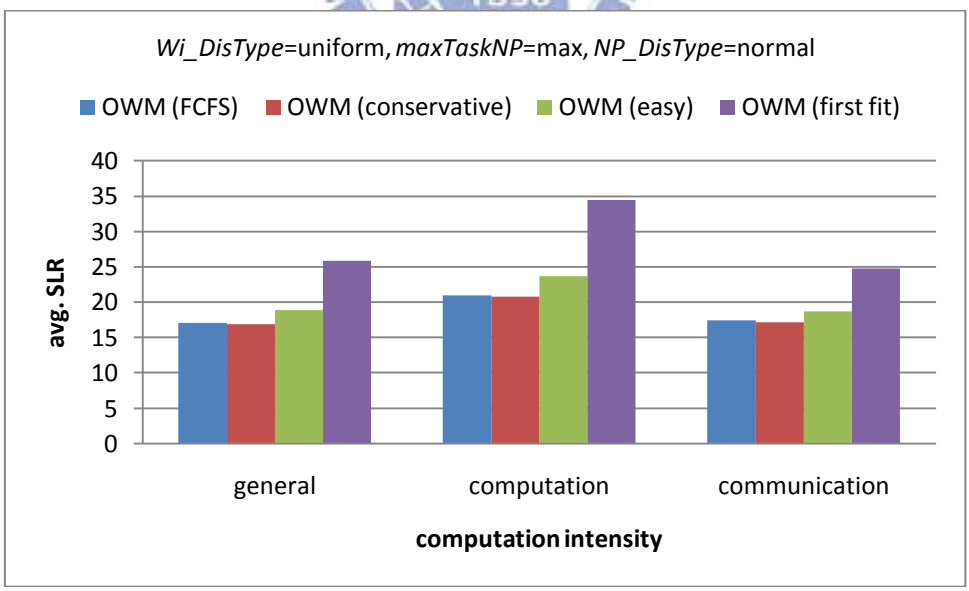


Figure A-8 Results of different computation intensity for average SLR with (uniform, max, normal)

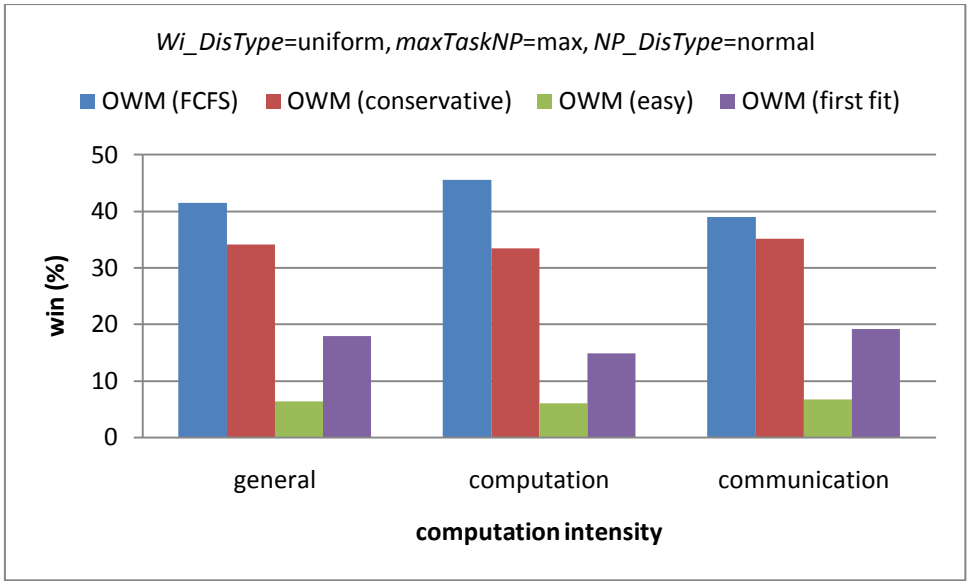


Figure A-9 Results of different computation intensity for win (%) with (uniform, max, normal)

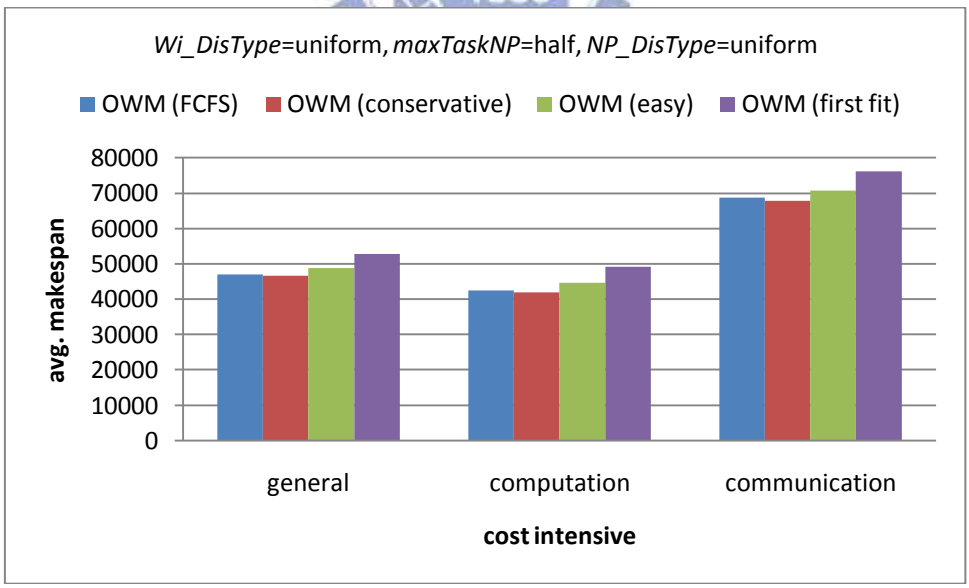


Figure A-10 Results of different computation intensity for average makespan with (uniform, half, uniform)

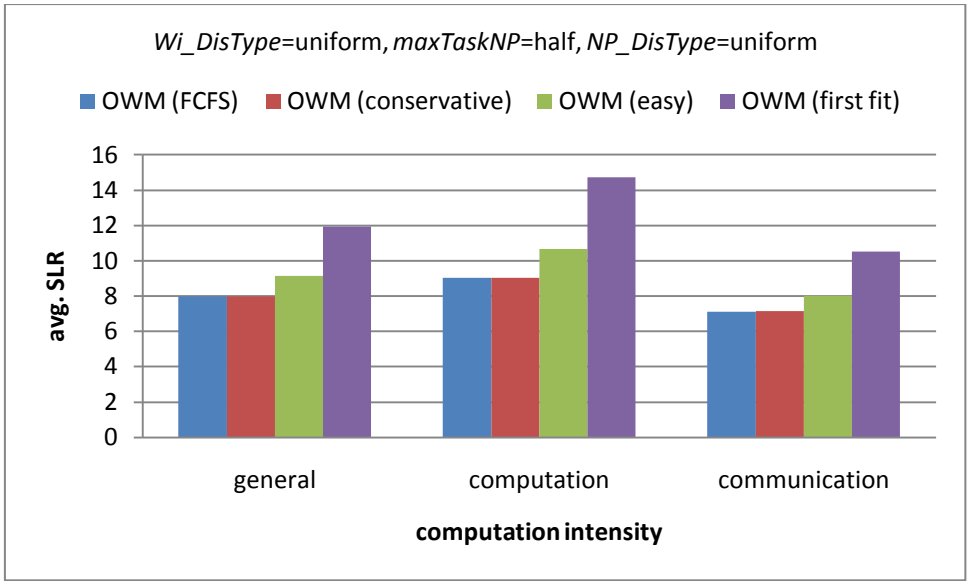


Figure A-11 Results of different computation intensity for average SLR with (uniform, half, uniform)

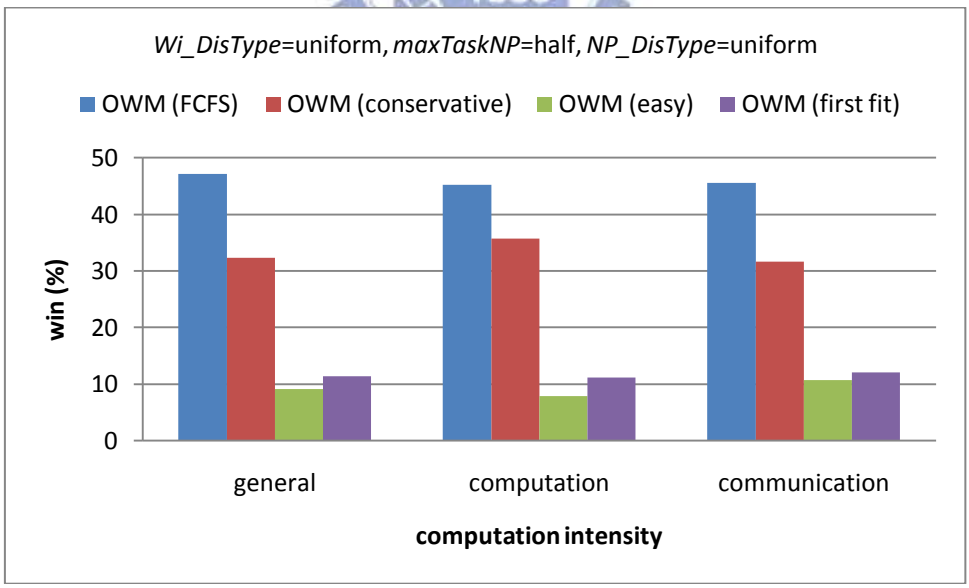


Figure A-12 Results of different computation intensity for win (%) with (uniform, half, uniform)

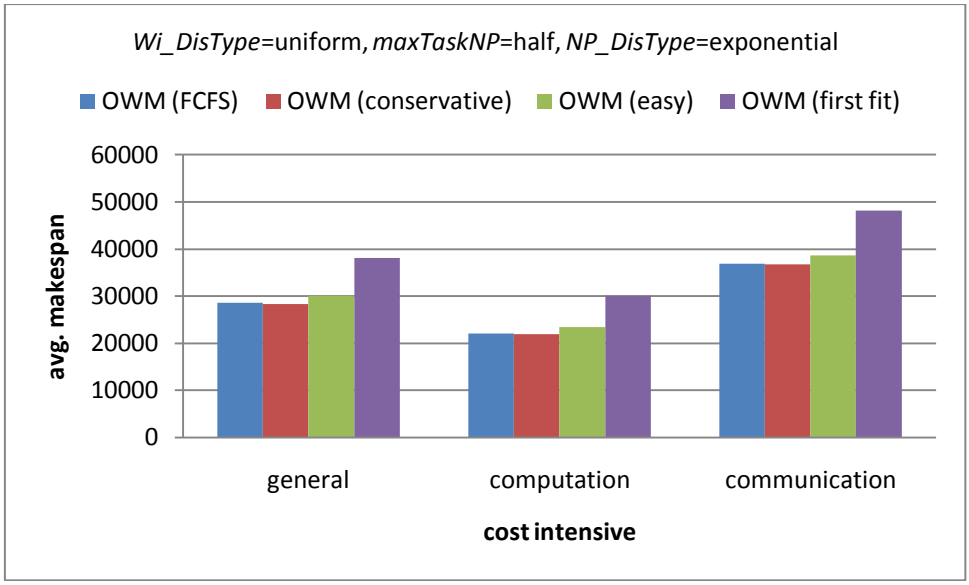


Figure A-13 Results of different computation intensity for average makespan with (uniform, half, exponential)

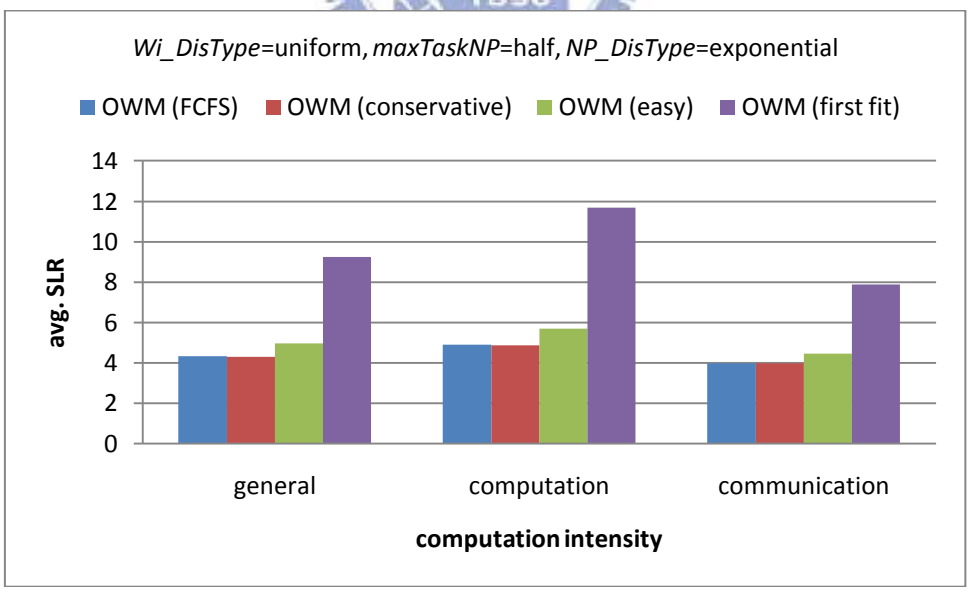


Figure A-14 Results of different computation intensity for average SLR with (uniform, half, exponential)

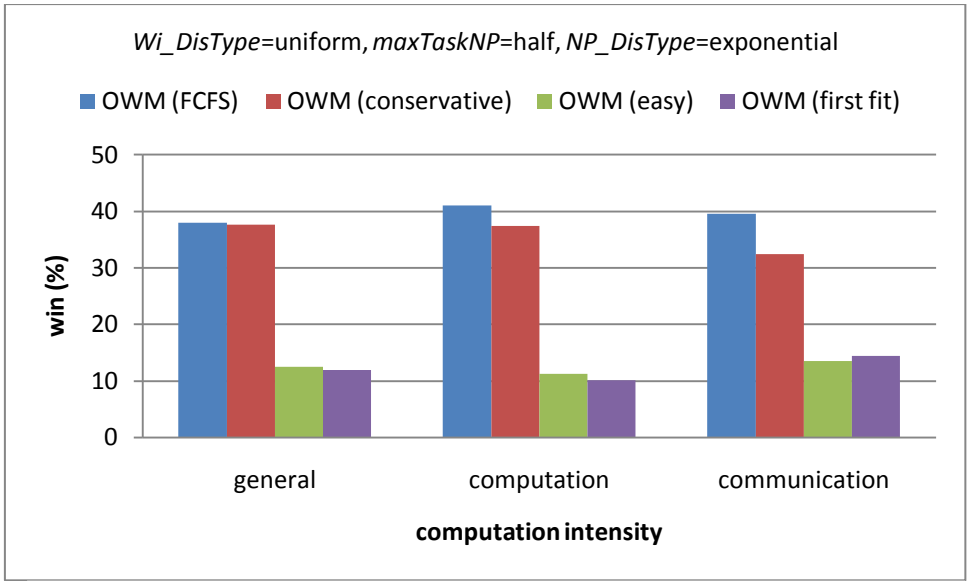


Figure A-15 Results of different computation intensity for win (%) with (uniform, half, exponential)

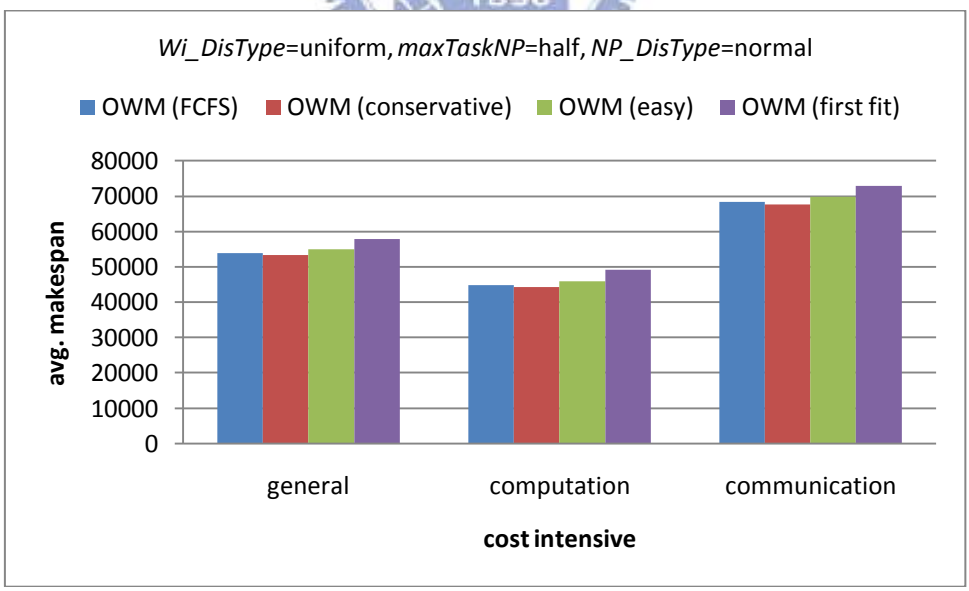


Figure A-16 Results of different computation intensity for average makespan with (uniform, half, normal)

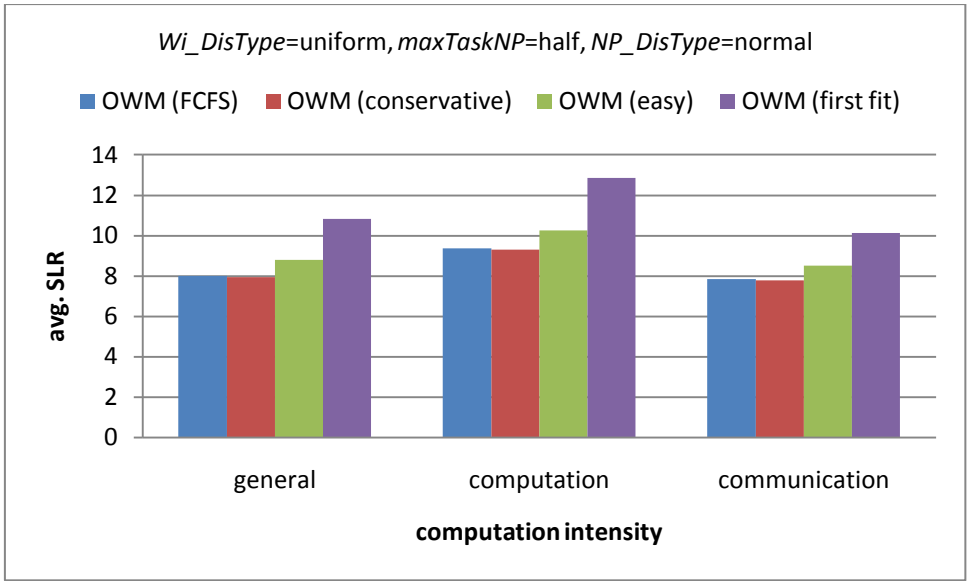


Figure A-17 Results of different computation intensity for average SLR with (uniform, half, normal)

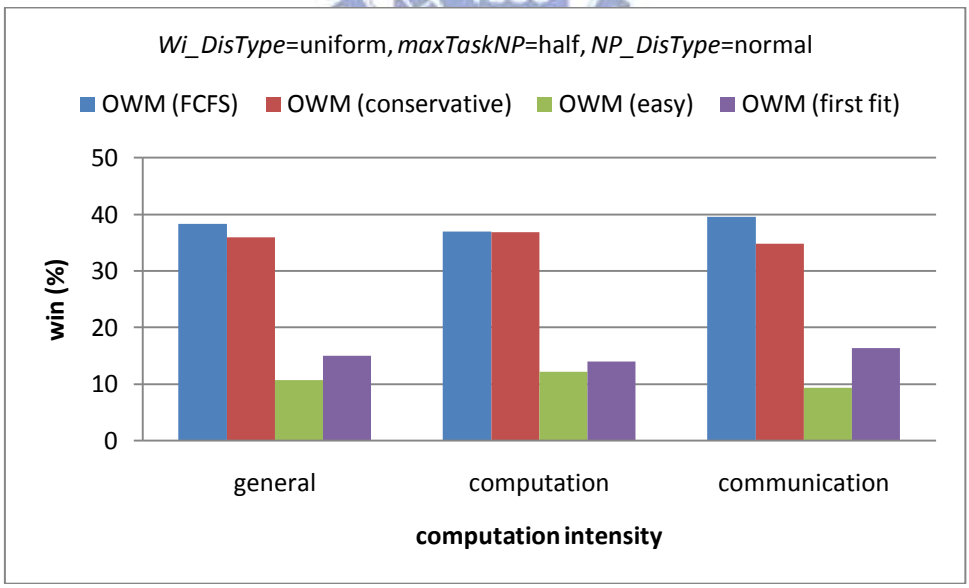


Figure A-18 Results of different computation intensity for win (%) with (uniform, half, normal)

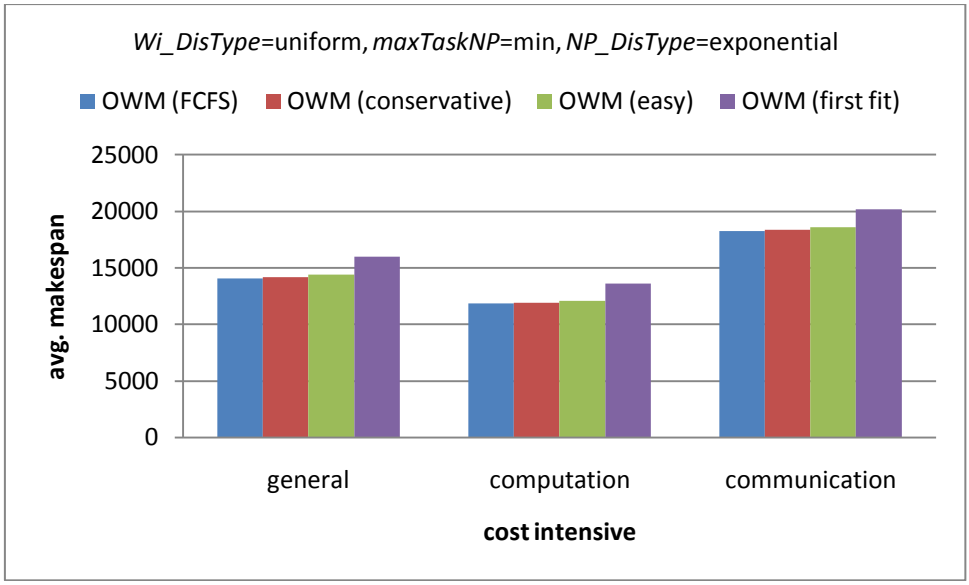


Figure A-19 Results of different computation intensity for average makespan with (uniform, min, exponential)

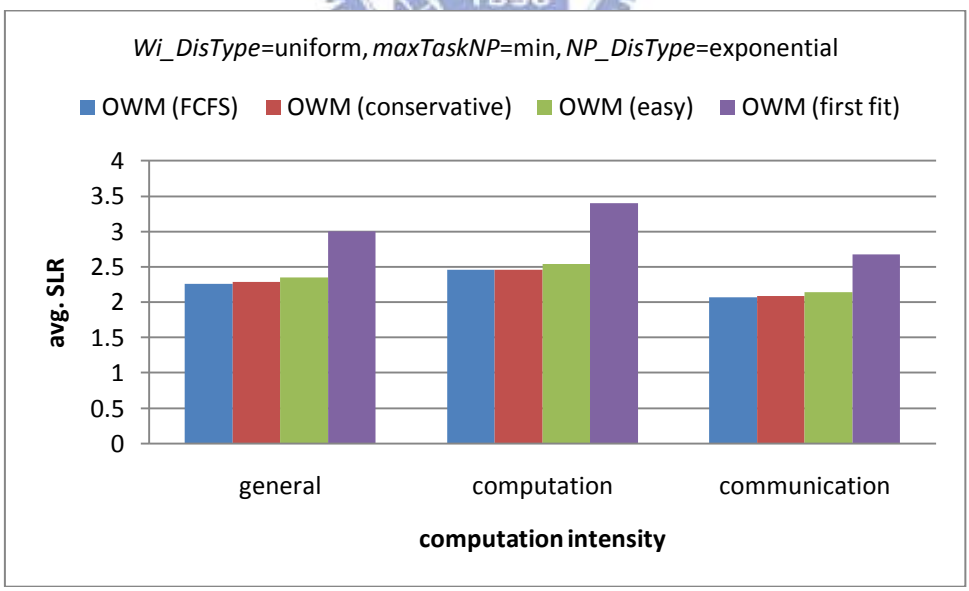


Figure A-20 Results of different computation intensity for average SLR with (uniform, min, exponential)

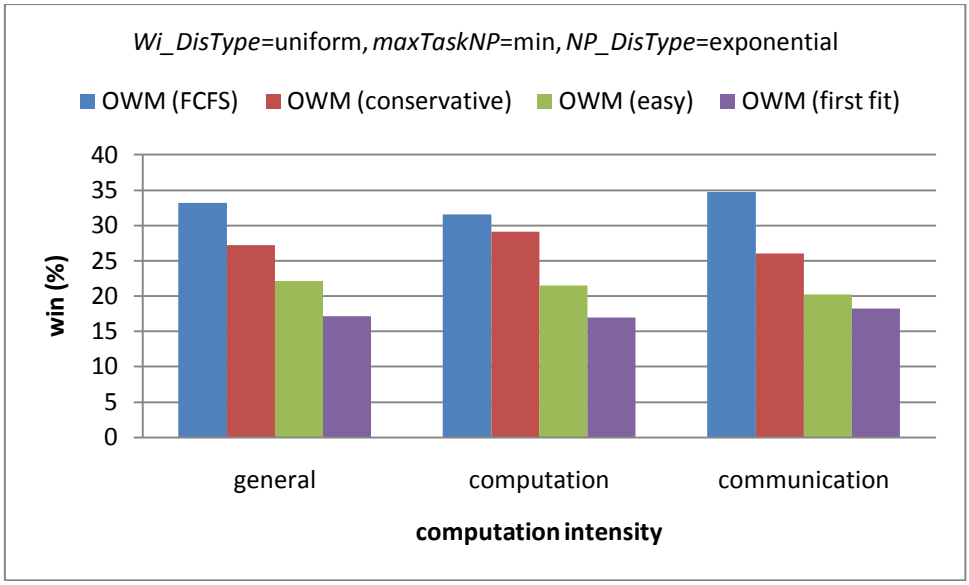


Figure A-21 Results of different computation intensity for win (%) with (uniform, min, exponential)

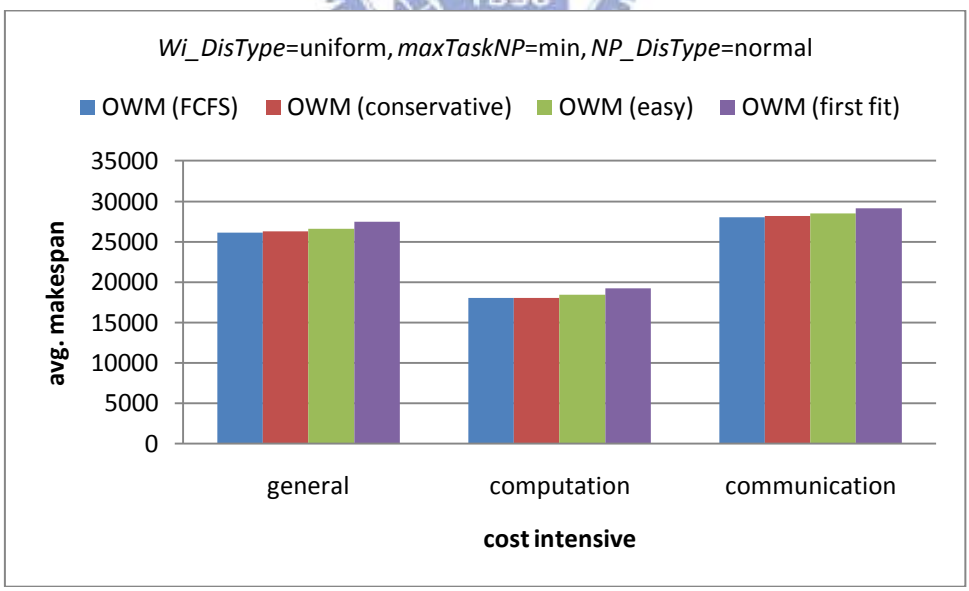


Figure A-22 Results of different computation intensity for average makespan with (uniform, min, normal)

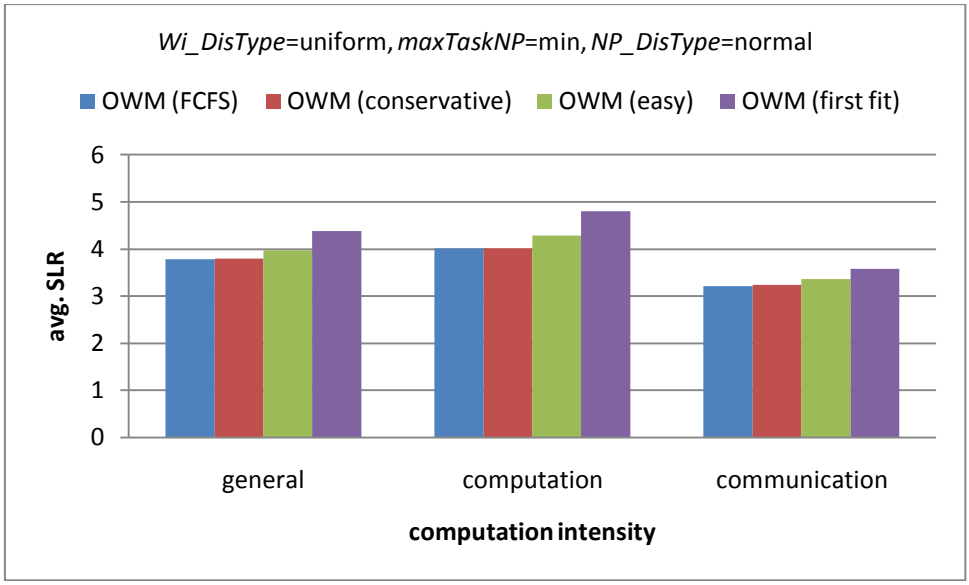


Figure A-23 Results of different computation intensity for average SLR with (uniform, min, normal)

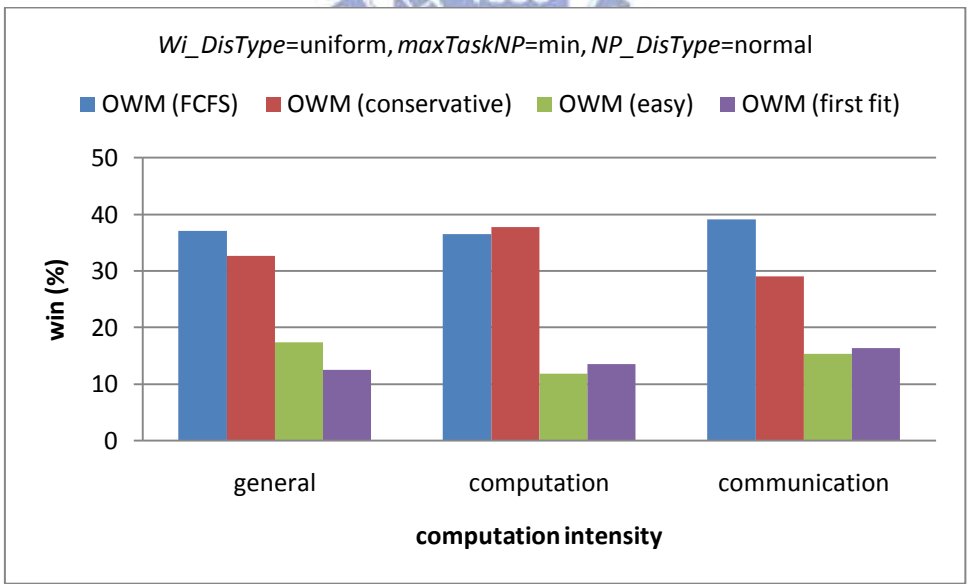


Figure A-24 Results of different computation intensity for win (%) with (uniform, min, normal)

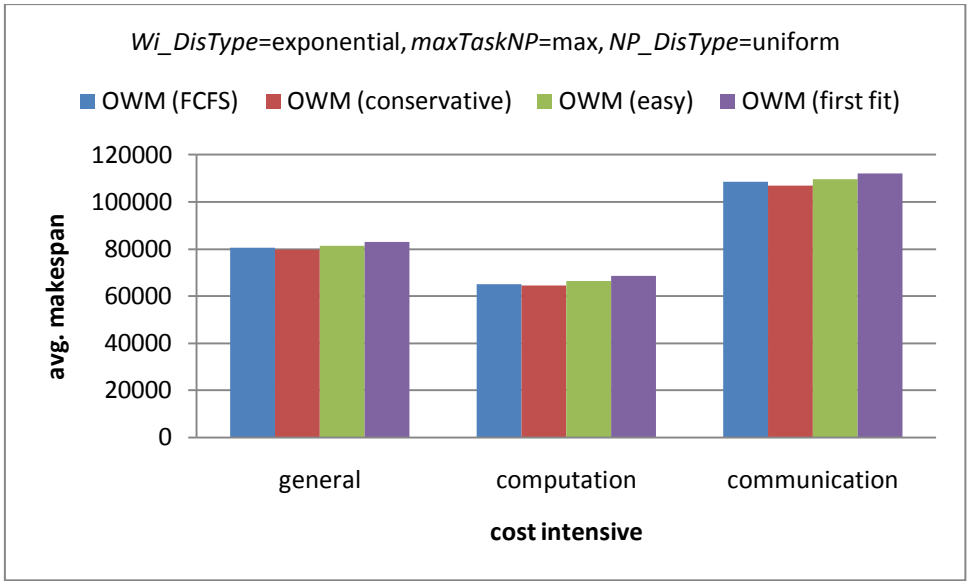


Figure A-25 Results of different computation intensity for average makespan with (exponential, max, uniform)

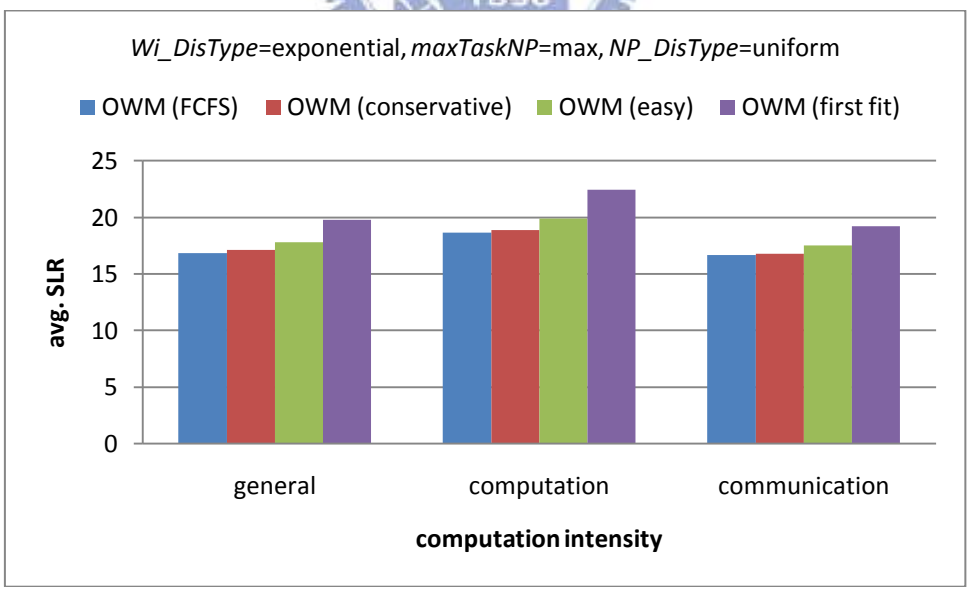


Figure A-26 Results of different computation intensity for average SLR with (exponential, max, uniform)

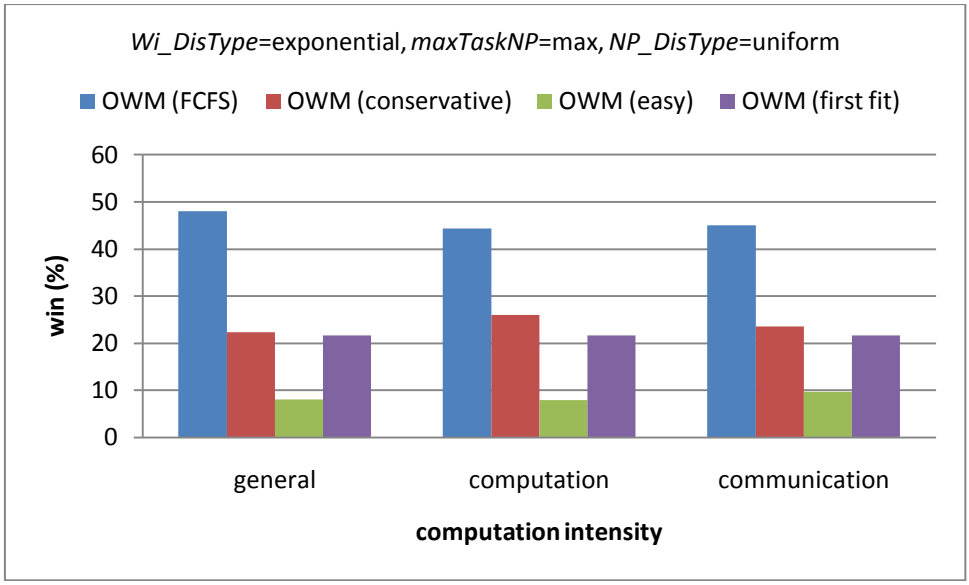


Figure A-27 Results of different computation intensity for win (%) with (exponential, max, uniform)

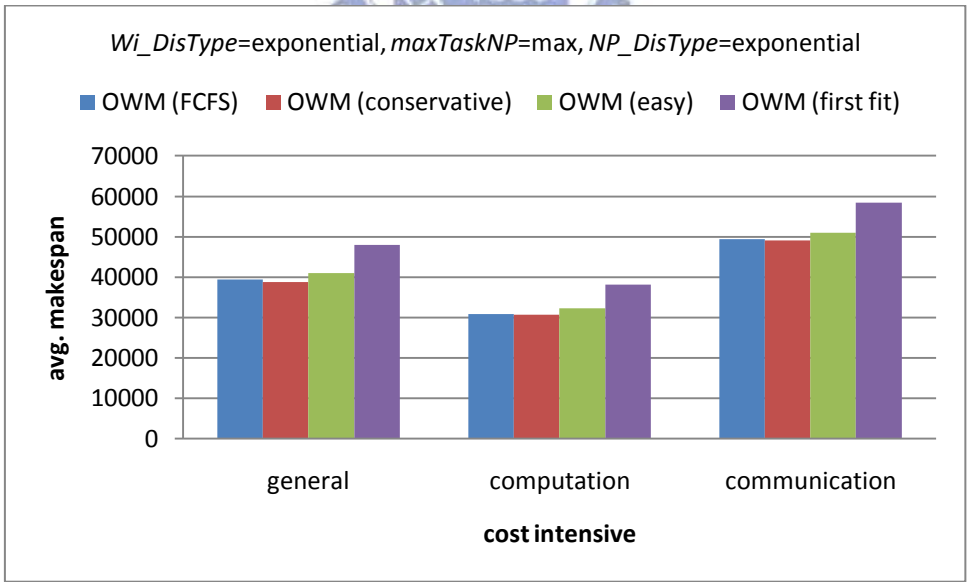


Figure A-28 Results of different computation intensity for average makespan with (exponential, max, exponential)

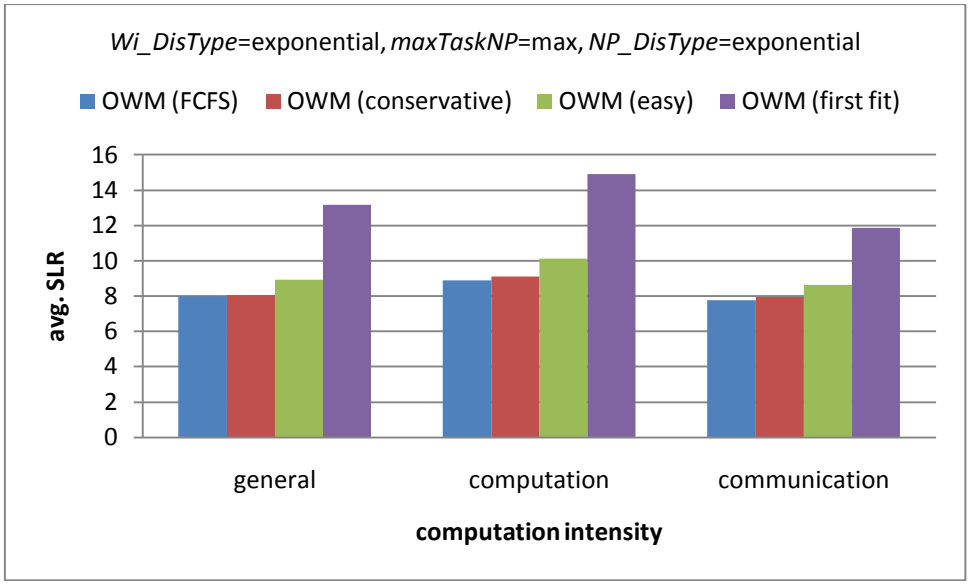


Figure A-29 Results of different computation intensity for average SLR with (exponential, max, exponential)

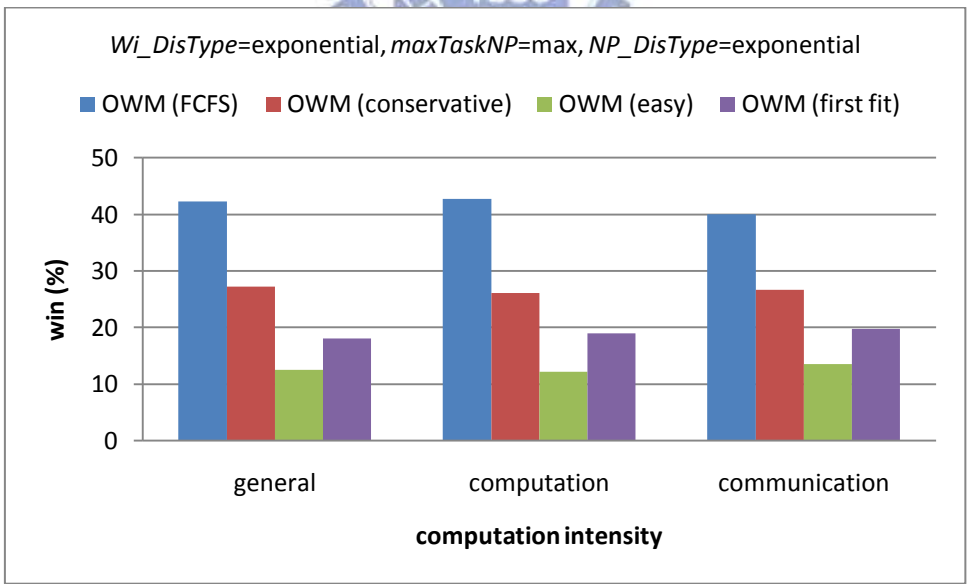


Figure A-30 Results of different computation intensity for win (%) with (exponential, max, exponential)

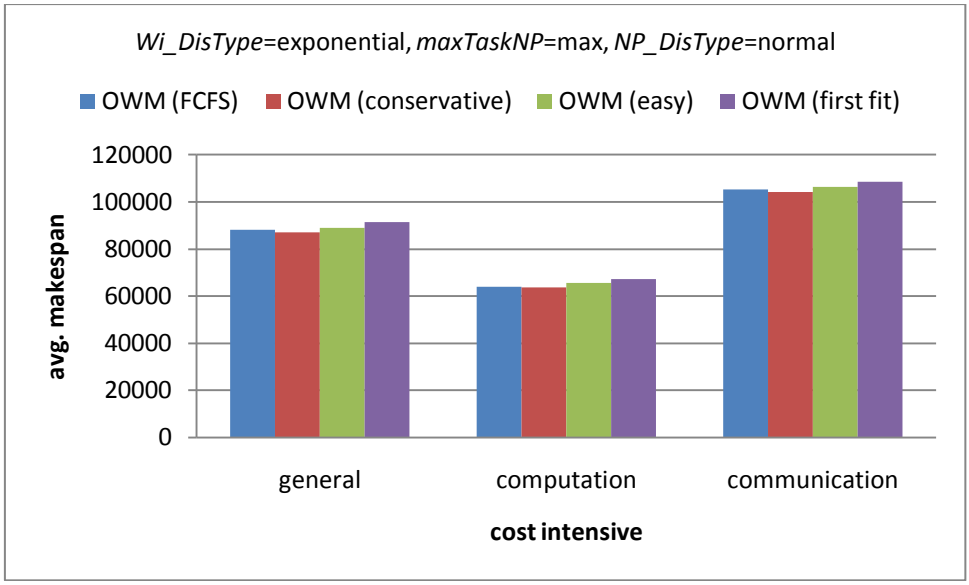


Figure A-31 Results of different computation intensity for average makespan with (exponential, max, normal)

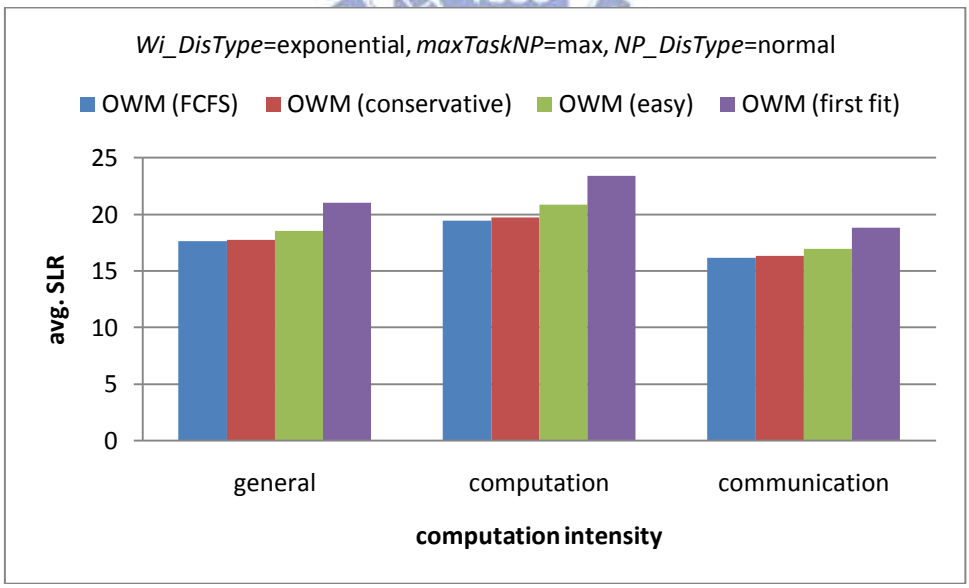


Figure A-32 Results of different computation intensity for average SLR with (exponential, max, normal)

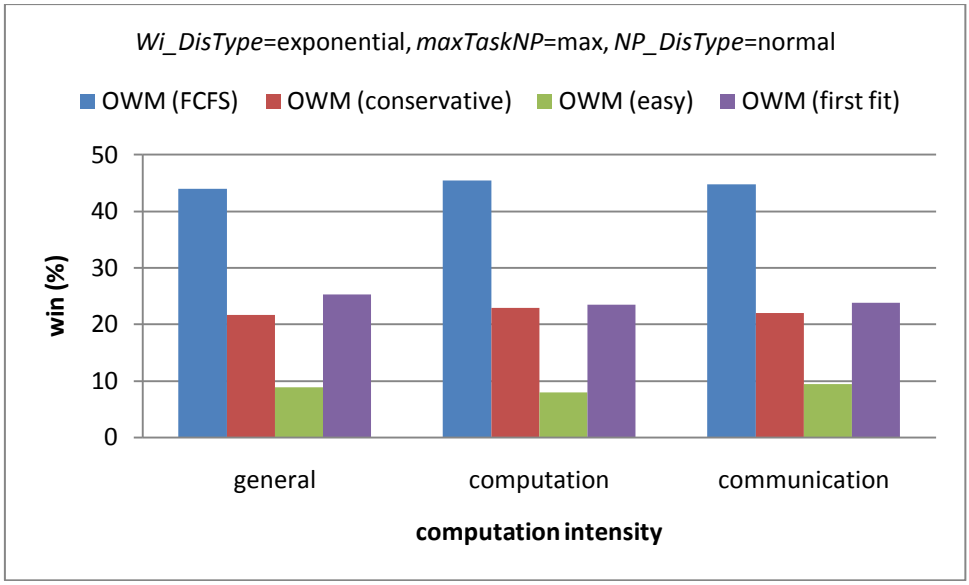


Figure A-33 Results of different computation intensity for win (%) with (exponential, max, normal)

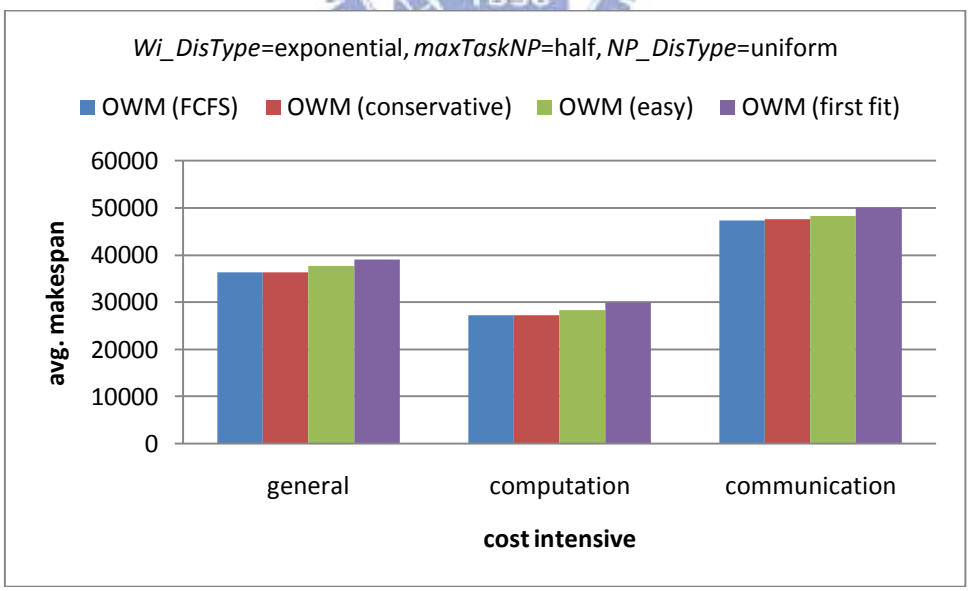


Figure A-34 Results of different computation intensity for average makespan with (exponential, half, uniform)

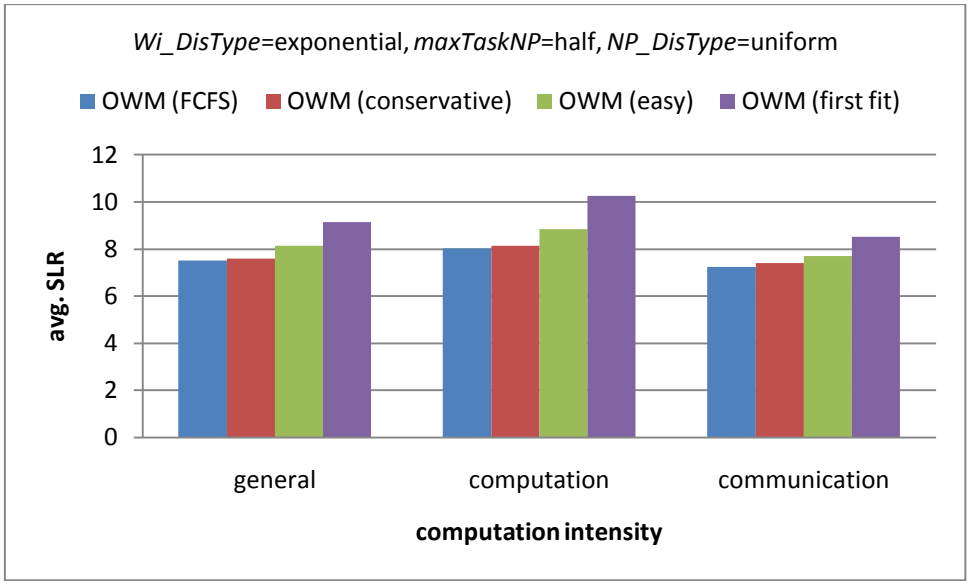


Figure A-35 Results of different computation intensity for average SLR with (exponential, half, uniform)

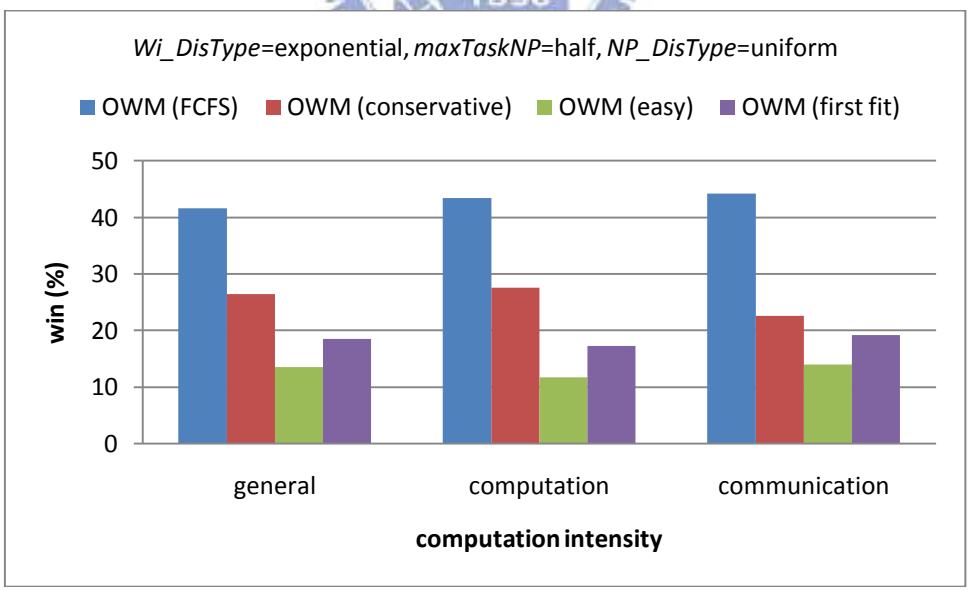


Figure A-36 Results of different computation intensity for win (%) with (exponential, half, uniform)

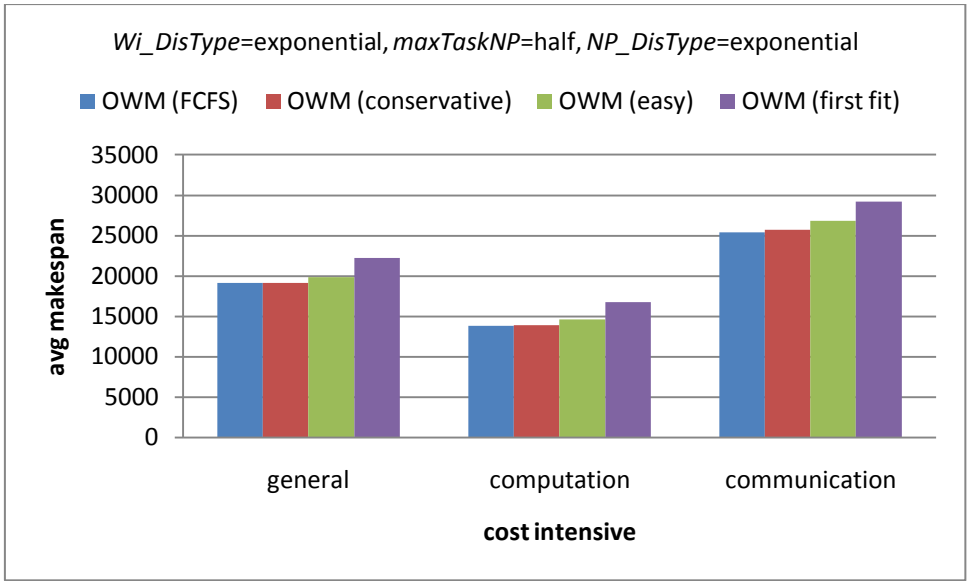


Figure A-37 Results of different computation intensity for average makespan with (exponential, half, exponential)

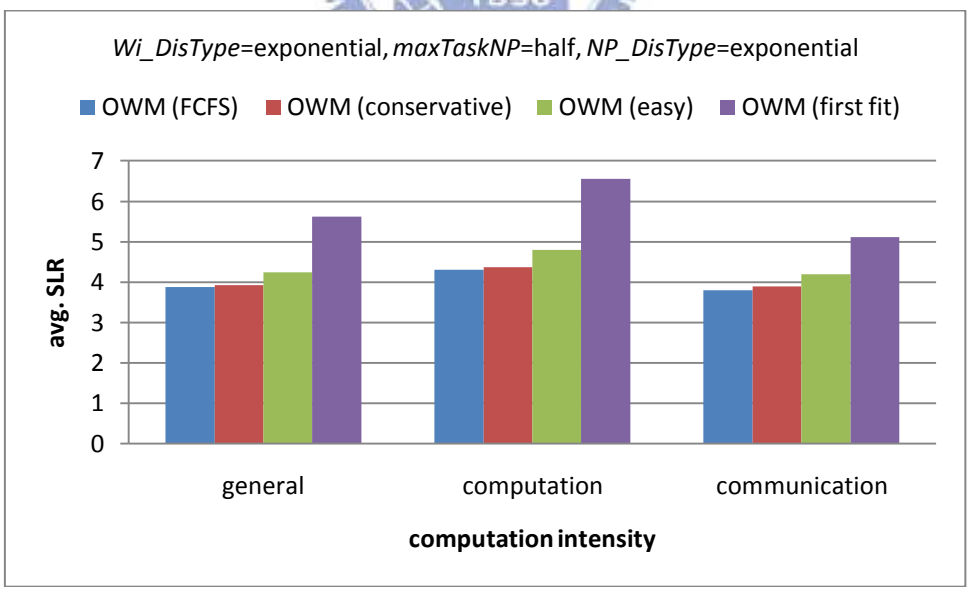


Figure A-38 Results of different computation intensity for average SLR with (exponential, half, exponential)

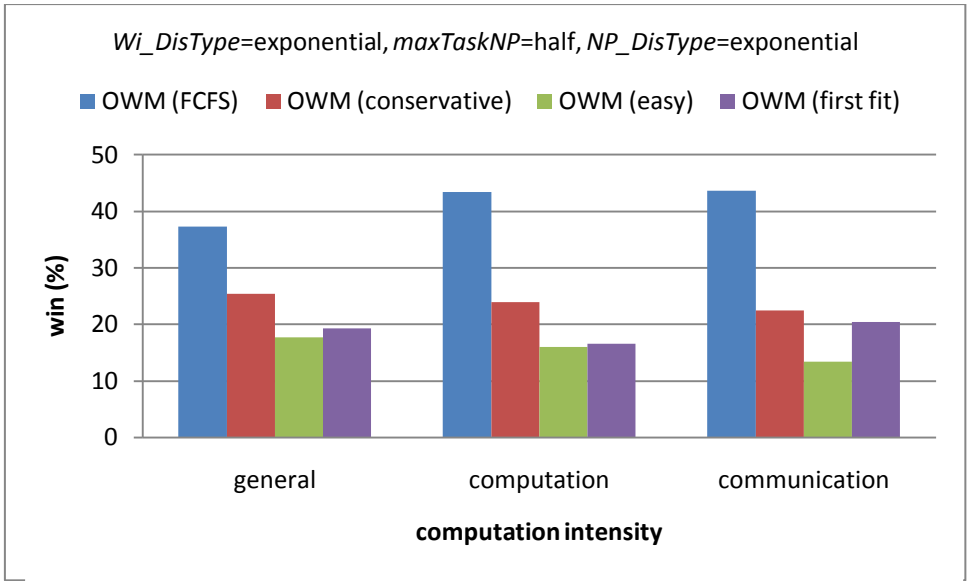


Figure A-39 Results of different computation intensity for win (%) with (exponential, half, exponential)

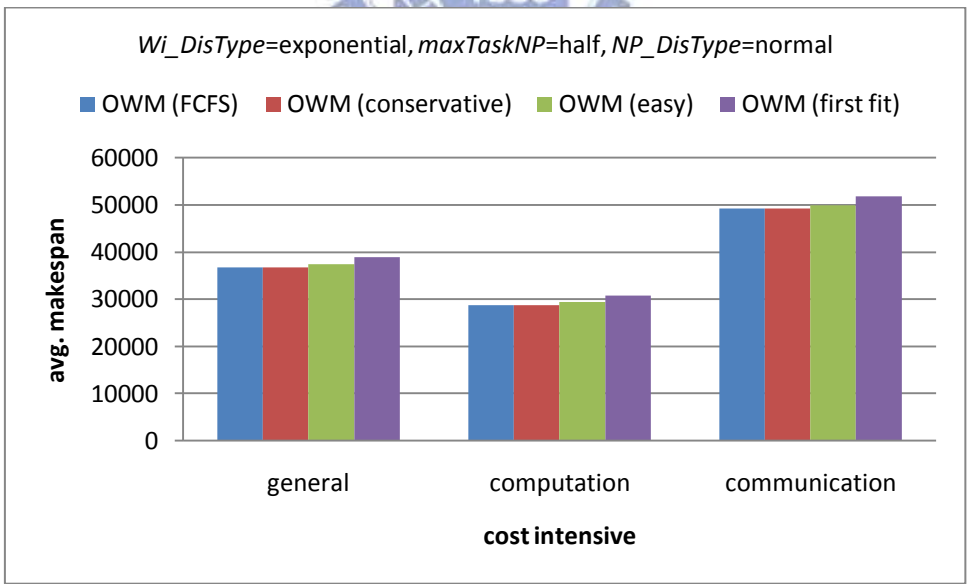


Figure A-40 Results of different computation intensity for average makespan with (exponential, half, normal)

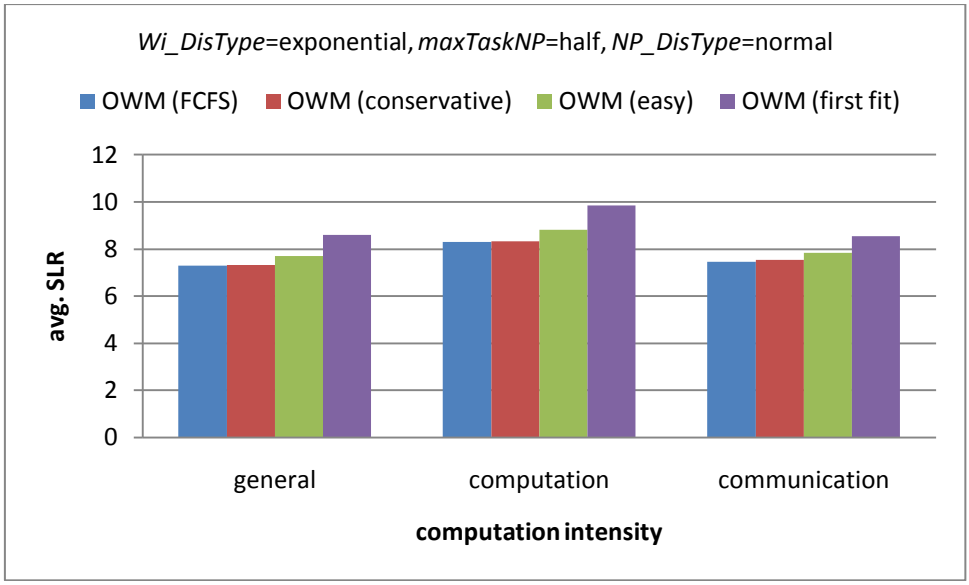


Figure A-41 Results of different computation intensity for average SLR with (exponential, half, normal)

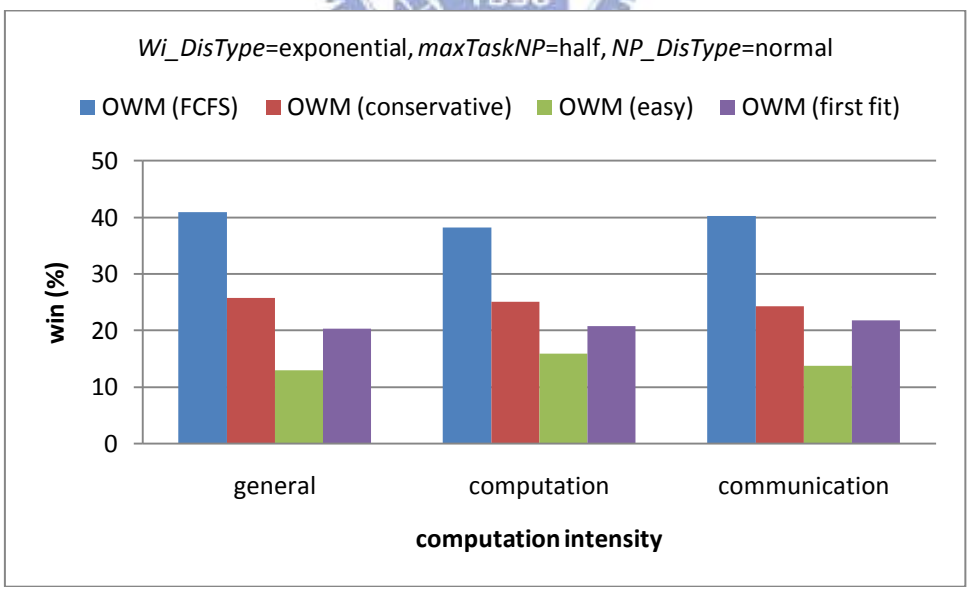


Figure A-42 Results of different computation intensity for win (%) with (exponential, half, normal)

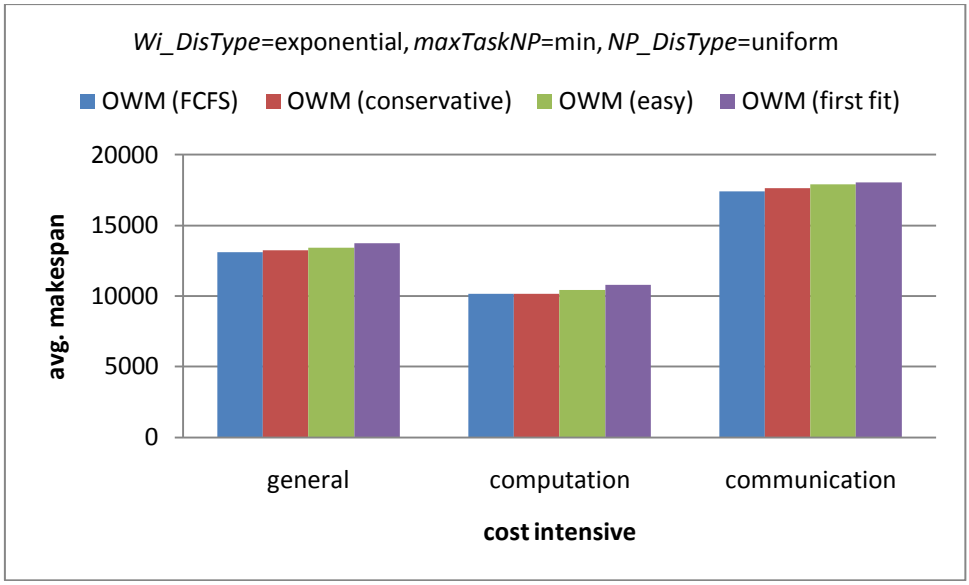


Figure A-43 Results of different computation intensity for average makespan with (exponential, min, uniform)

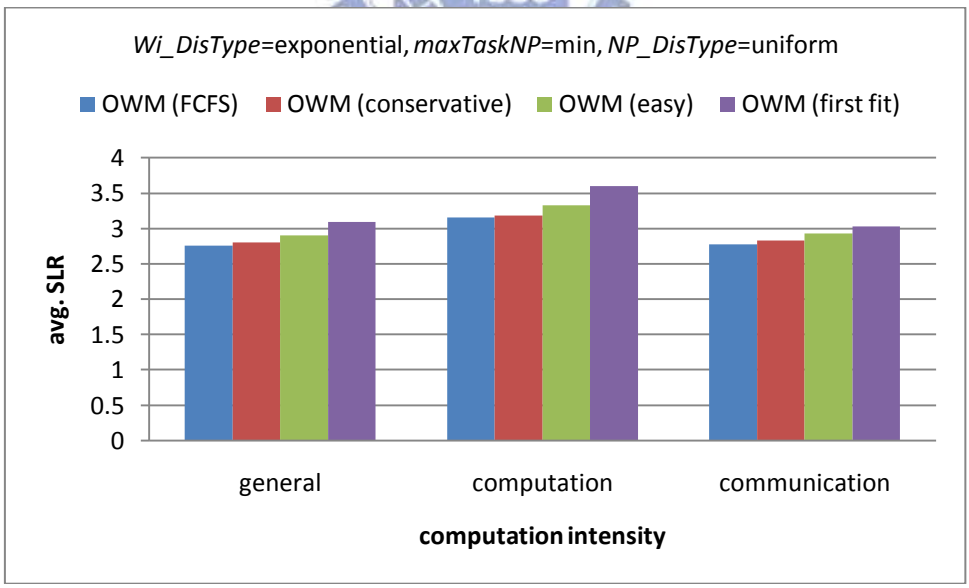


Figure A-44 Results of different computation intensity for average SLR with (exponential, min, uniform)

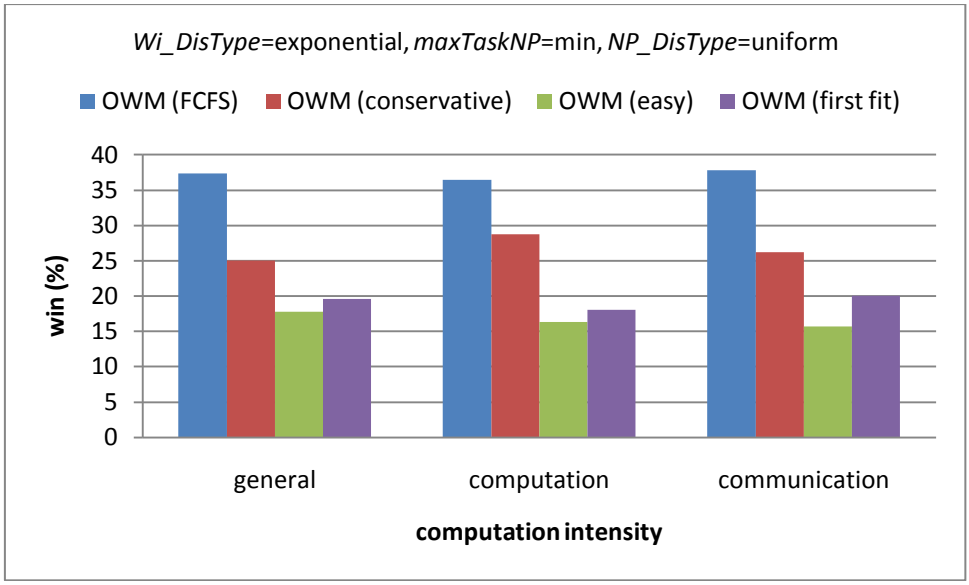


Figure A-45 Results of different computation intensity for win (%) with (exponential, min, uniform)

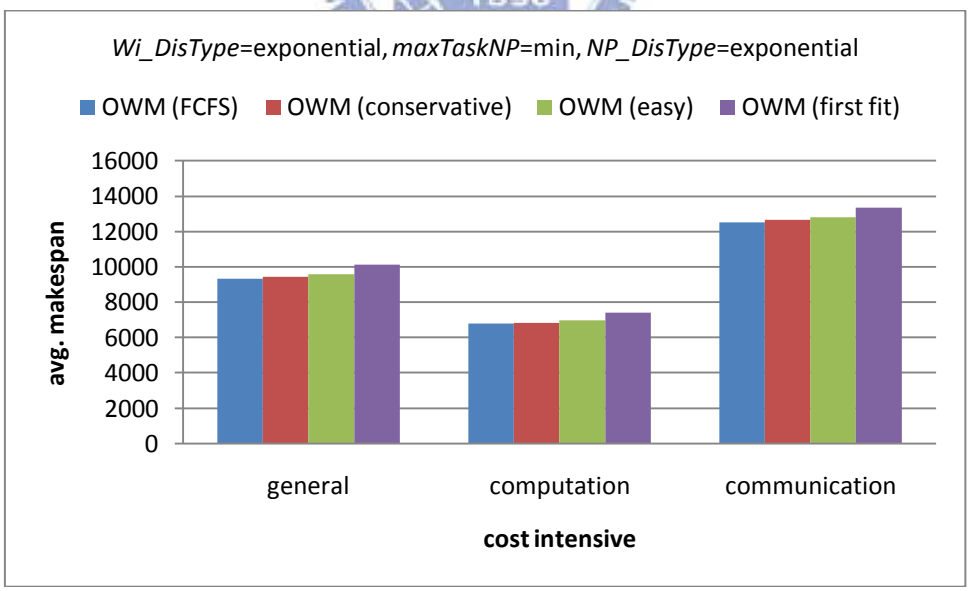


Figure A-46 Results of different computation intensity for average makespan with (exponential, min, exponential)

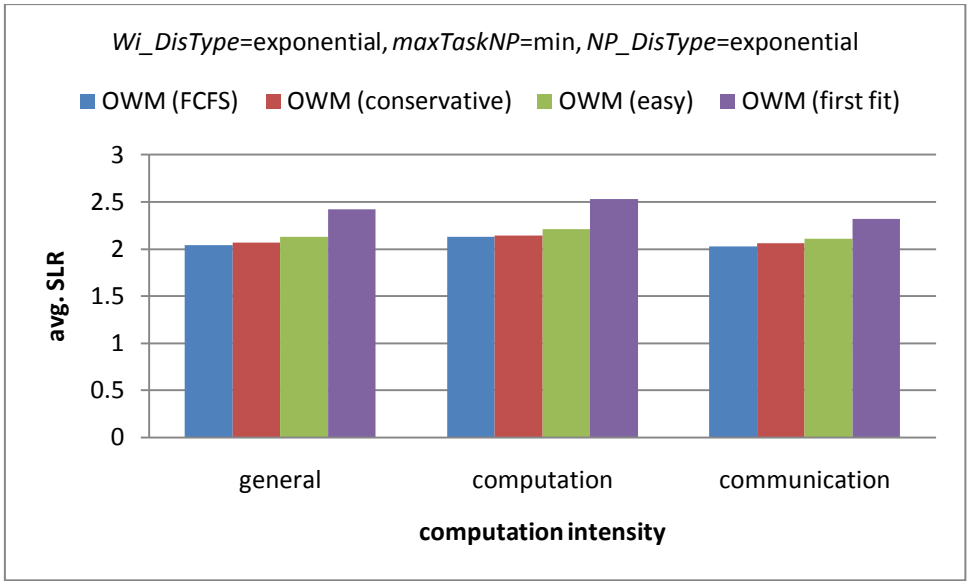


Figure A-47 Results of different computation intensity for average SLR with (exponential, min, exponential)

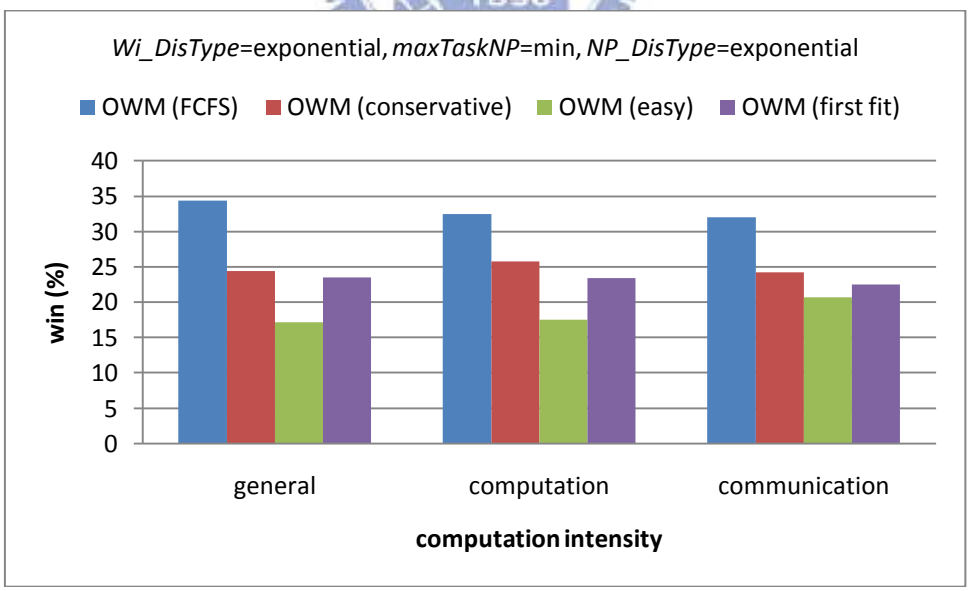


Figure A-48 Results of different computation intensity for win (%) with (exponential, min, exponential)

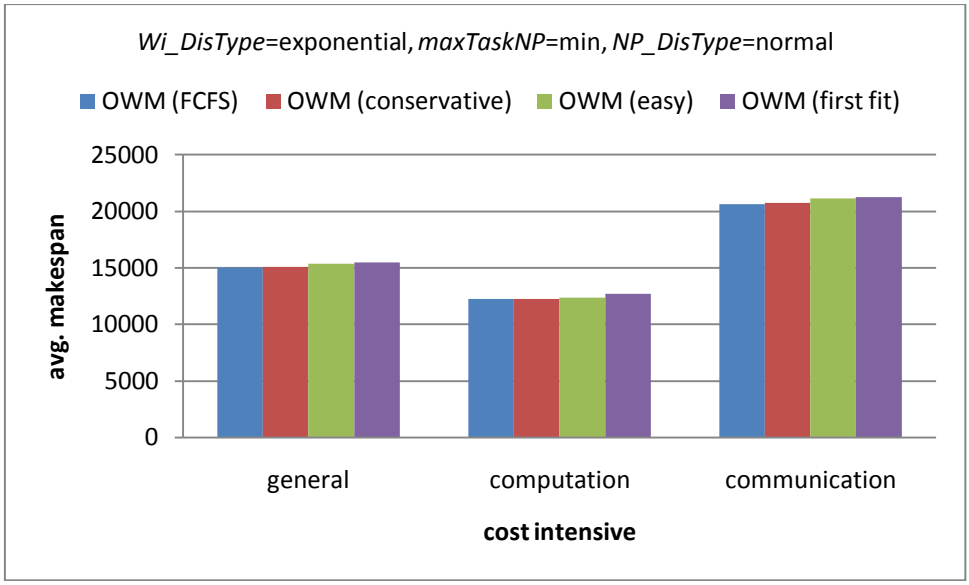


Figure A-49 Results of different computation intensity for average makespan with (exponential, min, normal)

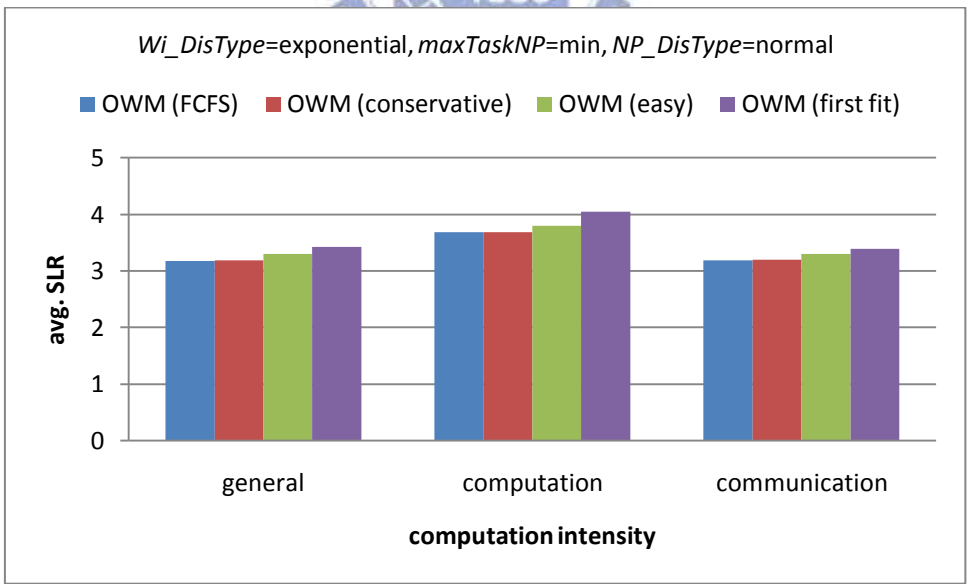


Figure A-50 Results of different computation intensity for average SLR with (exponential, min, normal)

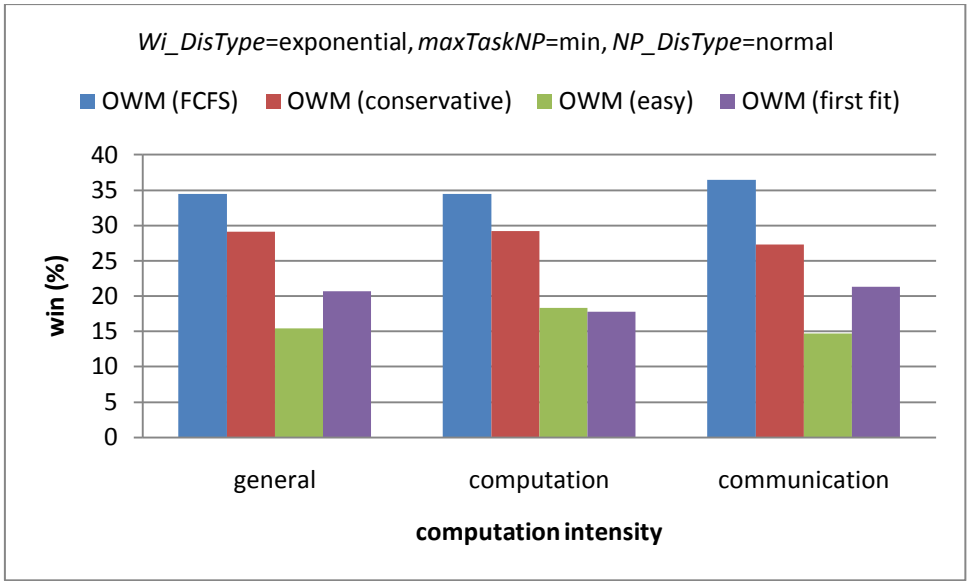


Figure A-51 Results of different computation intensity for win (%) with (exponential, min, normal)

Reference

[1] K. Cooper, A. Dasgupta, K. Kennedy, C. Koelbel, A. Mandal, G. Marin, M. Mazina, J. Mellor- Crummey, F. Berman, H. Casanova, A. Chien, H. Dail, X. Liu, A. Olugbile, O. Sievert, H. Xia, L. Johnsson, B. Liu, M. Patel, D. Reed, W. Deng, C. Mendes, Z. Shi, A. YarKhan and J. Dongarra, "*New Grid Scheduling and Rescheduling Methods in the GrADS Project"*, in Proc. of the 18th International Parallel and Distributed Processing Symposium (IPDPS'04), pp.199--206, Santa Fe, New Mexico USA, April 2004.

[2] T.D. Braun, H.J. Siegel, N. Beck, L.L. Bölöni, M. Maheswaran, A.I. Reuther, J.P. Robertson, M.D. Theys, B. Yao, D. Hensgen, R.F. Freund, "*A Comparison of Eleven Static Heuristics for Mapping a Class of Independent Tasks onto Heterogeneous Distributed Computing Systems"*, Journal of Parallel and Distributed Computing, Volume 61, Number 6, June 2001 , pp. 810-837(28).

[3] M. Wu and D. Gajski. " *Hypertool: A Programming Aid for Message Passing Systems*". IEEE Transactions on Parallel and Distributed Systems, vol. 1, pp. 330-343, July 1990.

[4] Y. Kwok and I. Ahmad. "*Dynamic Critical-Path Scheduling: An Effective Technique for Allocation Task Graphs to Multi-processors*". IEEE Transactions on Parallel and Distributed Systems, vol. 7, no. 5, pp. 506-521, May 1996.

[5] G.C. Sih and E.A. Lee. " *A Compile-Time Scheduling Heuristic for Interconnection-Constrained Heterogeneous Processor Architectures*". IEEE Transactions on Parallel and Distributed Systems, vol. 4, no. 2, pp. 175-186, Feb 1993.

[6] H. EI-Rewini and T.G. Lewis. "*Scheduling Parallel Program Tasks onto Arbitrary Target Machines*". J. Parallel and Distributed Computing, vol. 9, pp. 138-153, 1990.

[7] H. Topcuoglu, S. Hariri, and M.-Y. Wu. "*Performance-Effective and Low-Complexity Task Scheduling for Heterogeneous Computing*". IEEE Transactions on Parallel and Distributed Systems, 2(13):260-247, 2002.

[8] T. Yang and A. Gerasoulis. "*DSC: Scheduling Parallel Tasks on an Unbounded Number of Processors*". IEEE Transactions on Parallel and Distributed Systems, vol. 5, no. 9, pp. 951-967, Sept. 1994.

[9] G. Park, B. Shirazi, and J. Marquis. "*DFRN: A New Approach for Duplication Based Scheduling for Distributed Memory Multi-processor Systems*". Proc.

Int'l Conf. Parallel Processing, pp. 157-166, 1997.

[10] E. Deelman et al. "*Pegasus: Mapping Scientific Workflows onto the Grid*". In European Across Grids Conference, pp. 11-20, 2004.

[11] R. Sakellariou and H. Zhao. "*A Low-Cost Rescheduling Policy for Efficient Mapping of Workflows on Grid Systems*". Scientific Programming, 12(4), pp. 253-262, December 2004.

[12] M. Resende and C. Ribeiro. "*Greedy Randomized Adaptive Search Procedures, State-of-the-art Handbook in MetaHeuristics*". Glover and Kochenberger, eds., Kluwer Academic Publishers, 2002.

[13] H. Singh and A. Youssef. "*Mapping and Scheduling Heterogeneous Task Graphs Using Genetic Algorithms*". Proc. Heterogeneous Computing Workshop, pp. 86-97, 1996.

[14] A. YarKhan and J.J. Dongarra. "*Experiments with Scheduling Using Simulated Annealing in a Grid Environment*". In Grid 2002, November 2002.

[15] Y. Kwok and I. Ahmad, "*Benchmarking and comparison of the task graph scheduling algorithms",* Journal of Parallel and Distributed Computing, 59(3):381–422, 1999

[16] J. Blythe, S. Jain, E. Deelman, Y. Gil, K. Vahi, A. Mandal, K. Kennedy, "*Task Scheduling Strategies for Workflow-based Applications in Grid*". Cluster Computing and the Grid, 2005. CCGrid 2005. IEEE International Symposium**,** pp. 759-767 Vol. 2, 9-12 May 2005.

[17] J. Yu, R, Buyya, "*Workflow Scheduling Algorithms for Grid Computing*". Technical Report, Grid-TR-2007-10.

[18] R. Sakellariou and H. Zhao. "*A hybrid heuristic for DAG scheduling on heterogeneous systems*".In 18th International Parallel and Distributed Processing Symposium (IPDPS'04), page 111. IEEE Computer Society, 2004.

[19] H. Casanova, F. Desprez, and F. Suter. "*From Heterogeneous Task Scheduling to Heterogeneous Mixed Parallel Scheduling*". In 10th Int. Euro-Par Conference, volume 3149 of LNCS, pages 230-237, Aug. 2004.

[20] H. Zhao and R. Sakellarious. "*Scheduling Multiple DAGs onto Heterogeneous Systems*". In Proceedings of the 15th Heterogeneous Computing Workshop (HCW), Rhodes Island, Greece, April 2006.

[21] Z. Yu and W. Shi. "*A Planner-Guided Scheduling Strategy for Multiple Workflow Applications*". On Parallel Processing Workshops, ICPP-W 08, 8-12 Sept. 2008.

[22] A.W. Mu'alem and D.G. Feitelson. "*Utilization, Predictability, Workloads, and User Runtime Estimates in Scheduling the IBM SP2 with Backfilling*". IEEE Transactions on Parallel and Distributed Systems, vol. 12, no. 6, June 2001.

[23] T. N'takpe' and F. Suter. "*Concurrent Scheduling of Parallel Task Graphs on Multi-Clusters Using Constrained Resource Allocations*". Rapport de recherché n° 6774, December 2008.

[24] Y. Zhang, C. Koelbel, and K. Kennedy. "*Relative Performance of Scheduling Algorithms in Grid Environments*". In 7th IEEE International Symposium on Cluster Computing and the Grid (CCGrid 2007).

[25] A. Mandal, K. Kennedy, C. Koelbel, G. Marin, J. Mellor-Crummey, B. Liu, and L. Johnsson. "*Scheduling Strategies for Mapping Application workflows onto the Gird*". In 14th IEEE Symposium on High Performance Distributed Computing (HPDC 14), pp. 125-134, 2005.

[26] F. Dong and S.G. Akl. "*Scheduling Algorithms for Grid Computing: State of the Art and Open Problems*". Technical Report No. 2006-504.

[27] E. Deelman, G. Singh, and C. Kesselman. "*Optimizing Grid-based Workflow Execution*". Journal of Grid Computing, 3(3): 201-219, 2005.

[28] T. N'takpe' and F. Suter. "*A Comparison of Scheduling Approaches for Mixed-Parallel Applications on Heterogeneous Platforms*". In 6th International Symposium on Parallel and Distributed Computing (IS-PDC), pp. 250-257, Hagenberg, Austria, July 2007.

[29] G. Singh, E. Deelman, and G. Bruce Berriman et al. "*Montage: a Grid Enabled Image Mosaic Service for the National Virtual Observatory*". Astronomical Data Analysis Software and Systems (ADASS), (13), 2003.

[30] S. Ludtke, P. Baldwin, and W. Chiu. "*EMAN: Semiautomated Software for High Resolution Single-Particle Reconstructions*". J. Struct. Biol, (128): 82-97, 1999.

[31] M.R. Gary and D.S. Johnson. "*Computers and Intractability: A Guide to the Theory of NP-Completeness*". W.H. Freeman and Co., 1979.

[32] J.D. Ullman. "*NP-Complete Scheduling Problems*". J. Computer and Systems Sciences, vol. 10, pp. 384-393, 1975.

[33] Miguel L. Bote-Lorenzo, Yannis A. Dimitraidis, and Eduardo Gomez-Sanchez. "*Grid Characteristics and uses: a Grid Definition*".