Robust and Fault-Tolerant Scheduling for Scientific Workflows in Cloud Computing Environments

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Abstract

CLOUD environments offer low-cost computing resources as a subscription-based service. These resources are elastically scalable and dynamically provisioned. Furthermore, new pricing models have been pioneered by cloud providers that allow users to provision resources and to use them in an efficient manner with significant cost reductions. As a result, scientific workflows are increasingly adopting cloud computing. Scientific workflows are used to model applications of high throughput computation and complex large scale data analysis.

However, existing works on workflow scheduling in the context of clouds are either on deadline or cost optimization, ignoring the necessity for robustness. Cloud is not a utopian environment. Failures are inevitable in such large complex distributed systems. It is also well studied that cloud resources experience fluctuations in the delivered performance. Therefore, robust and fault-tolerant scheduling that handles performance variations of cloud resources and failures in the environment is essential in the context of clouds.

This thesis presents novel workflow scheduling heuristics that are robust against performance variations and fault-tolerant towards failures. Here, we have presented and evaluated static and just-in-time heuristics using multiple fault-tolerant techniques. We have used different pricing models offered by the cloud providers and proposed schedules that are fault-tolerant and at the same time minimize time and cost. We have also proposed resource selection policies and bidding strategies for spot instances. The proposed heuristics are constrained by either deadline and budget or both. These heuristics are evaluated with the prominent state-of-the art workflows.

Finally, we have also developed a multi-cloud framework for the Cloudbus workflow

management system, which has matured with years of research and development at the CLOUDS Lab in the University of Melbourne. This multi-cloud framework is demonstrated with a private and a public cloud using an astronomy workflow that creates a mosaic of astronomic images.

In summary, this thesis provides effective fault-tolerant scheduling heuristics for workflows on cloud computing platforms, such that performance variations and failures can be mitigated whilst minimizing cost and time.

Declaration

This is to certify that

1. the thesis comprises only my original work towards the PhD,
2. due acknowledgement has been made in the text to all other material used,
3. the thesis is less than 100,000 words in length, exclusive of tables, maps, bibliographies and appendices.

Deepak Poola Chandrashekar, August 2015

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"It was my luck to have a few good teachers..., men and women who came into my dark head and lit a match."

-Yann Martel, author, Life of Pi (Chapter 7)

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Deepak Poola Chandrashekar

August 2015

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To my mother, who created in me an eternal hunger to learn.

ಕೆಲವಂ ಬಲ್ಲವರಿಂದ ಕಲ್ತು
ಕೆಲವಂ ಮಳ್ಪವರಿಂದ ಕಂಡು ಮತ್ತೆ
ಹಲವಂ ತಾನೆ ಸ್ವತಃಮಾಡಿ ತಿಳಿ ಎಂದ ಸರ್ವಜ್ಞ II

Transliteration

Kelavam ballavarindha kaltu
Kelavam malpavarindha kandu matthe
Halavam thaane swathaha maadi thilli endha sarvagna II

Summary

Sarvajña is an eminent Indian poet and philosopher from the state of Karnataka, believed to be from the 16th century. The word "Sarvajña" in Sanskrit literally means "the one who knows everything". He is famous for his three-line poems called *vachanas* like the one above.

In this *vachana,* Sarvajña points outs that we cannot learn everything in this world by ourselves. **He advocates the best way to learn is to listen to those who know, watch the actions of those who do and then do the rest by yourself and learn**. This in many ways, I believe, is the essence of research.

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Chapter 1

Introduction

OVER the last few decades, the experimentation methodology in science has changed significantly. In particular, tremendous increases in the computational capacities have enabled deeper and more accurate research within the community. As scientific research tends to become more complex involving large scale datasets, a scalable and automated way to perform these computations and data processing is necessary. This experimentation typically involves transferring data to a compute node (or computation to data nodes), running the computations, analysing the results, and managing the storage of output results. Workflow Management Systems (WFMSs) aim to automate this entire process, making it easier and more efficient for researchers [41].

A primitive science of workflow design initially emerged within the business world. They used this concept to automate their business logic and tools. This was later borrowed into the scientific domain. The automation process involves a sequence of *tasks* and their *dependencies* to conduct a business or scientific work. This process is called *workflow orchestration*. An instance of a workflow orchestration is called a *workflow* [41]. That is, workflow is an application composed of a collections of tasks, which are most frequently executable scripts taking input data and producing output data. These tasks are connected by data and/or control dependencies as illustrated in Figure 1.1. Data dependencies define the flow of data within a workflow application. Normally, when two tasks are data dependent, then the output of the first task becomes the input of the second task, and the second task starts its execution after the first task finishes execution, writes the output data, and stages the data in the location of the second task. Similarly, the control dependencies define the sequence of executions for the tasks. Therefore, workflows

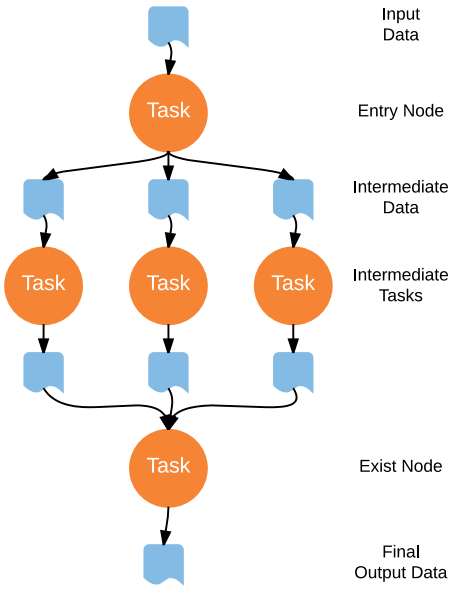


Figure 1.1: A sample workflow, depicting tasks, data, and their dependencies.

express the relationship between individual tasks and their input and output data in an explicit way. They link together computational tasks such that they can be reliably and automatically executed on behalf of the researchers [75].

The early workflow systems both in business and science were described with complex job-control languages and shell scripts. These scripts required substantial preprocessing and post-processing to manage and run a workflow, making the scripting approach sophisticated. With the introduction of distributed systems for scientific applications, scripts could no longer control and coordinate workflow executions. To deal with these environments, WFMSs had to evolve into systems built around remote procedure calls, distributed object technology, and distributed file systems and databases. These approaches slowly evolved into grid technologies, web service-oriented architectures, and now cloud technologies [41].

Currently, workflows are a prevalent paradigm for managing and representing complex distributed computations. In addition to automation, they provide the information necessary for scientific reproducibility, result derivation, and sharing among collaborators [61]. By providing automation and enabling reproducibility, they can accelerate and transform the scientific analysis process. Workflows are deployed in diverse distributed

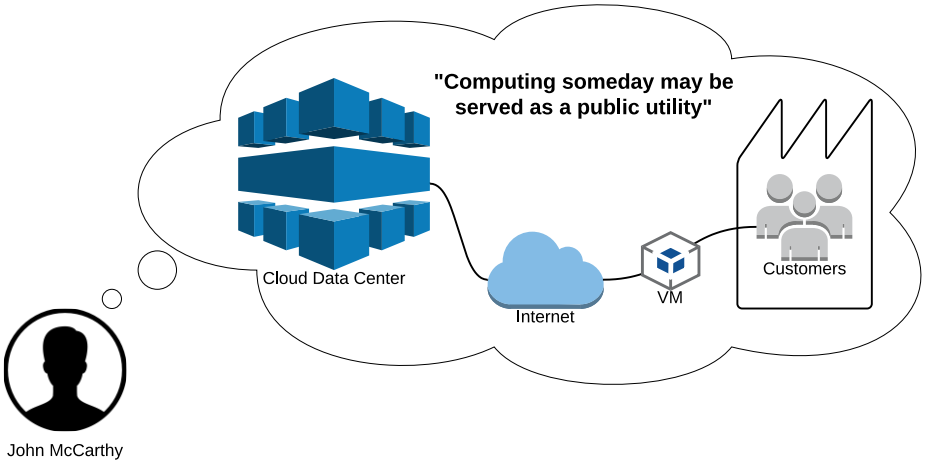


Figure 1.2: Vision of cloud computing by John McCarthy.

environments, starting from supercomputers and clusters, to grids and currently cloud computing environments [61,75]. As a subscription-based computing service, cloud computing provides a convenient platform for scientific workflows, because it offers virtualized servers, which are dynamically managed, monitored, maintained, and governed by market principles. In the next section, we introduce the notion of cloud computing, its origins, features and benefits.

1.1 Introduction to Cloud Computing

Enterprises over decades have invested in expensive hardware in anticipation of a peak load that might occur occasionally or seasonally. Unfortunately, most of these servers sit idle for long periods of the year. Alternatively, hardware needs to be upgraded every few years to keep pace with new technology. These capital costs make it extremely difficult for small and medium companies to commercialize their ideas and bring them to market.

However, other utilities such as energy, gas and water are not generated in the premises. These utilities are consumed by us on-demand and we pay for what we use.The science and technology behind how these utilities are delivered to us is not of paramount importance. The provision of these services as utilities sparked an economic and social revolution, making it relatively more affordable for common people and fostering innovation built on these fundamental building blocks.

In 1960 John McCarthy envisioned (Figure 1.2) that computation someday would be provided as an utility [115]. Cloud computing is the realization of this vision. With technologies such as Web Services, Service Oriented Architecture, Web 2.0, Mashups and Hardware Virtualization becoming popular and widely accepted, they were laying the path for cloud computing environments.

Cloud computing sprung up as an amalgamation of these technologies. New business models centered around it made it an economical option for small and medium enterprises. Cloud computing is formally defined by NIST (National Institute of Standards and Technology) as "A model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction." [99].

Cloud computing is subscription-based service that delivers computation as a utility. The key characteristics of this service that is making it rapidly popular are:

- Delivered on demand: cloud providers paint an illusion of unlimited resources[1]. They promise to lease these resources on-demand dynamically as users make requests through easy interfaces and programmable APIs.

- Pay-as-you-go: cloud users pay only for the time they used the resources, much like other utility services. Cloud providers may have different pricing models, such as, Amazon charges per hour whereas, Google compute engine charge per minute. But the user pays for only the approximate period they used the resources.

  Cloud computing is highly driven by market principles. Economics drive the cloud and competition among providers drive the pricing of cloud resources. Cloud computing envisions computing as a commodity and builds business models and services around this philosophy.

- Attractive and innovative pricing models: Clouds providers have different pricing models. As stated earlier, different cloud providers price differently and a single cloud provider can provision the same resource through multiple pricing models.

[1] In this thesis, resources, instances and VMs are used interchangeably.

For example, Amazon EC2 instances are provisioned in three main ways: 1) on-demand instance, where the user pays per hour. 2) spot instances: where a user bids for the instance and if the bidding price is higher than the spot price then the instances are leased to the user. And when the bid price fall below spot price, the instance is terminated. 3) reserved instance, here, the user pays an upfront price and reserves the instance for a period of time. Further, when they actually use the instance they pay an additional nominal price for the same.

- Highly elastic: Cloud resources can be leased and shut down when the user pleases. This gives users flexibility to scale up and down as their application demands.

- Provide different levels of services: Clouds providers provision cloud resources through various levels of services, such as, 1) infrastructure-as-a-service: where resources like storage, virtual machine, and network are provisioned. 2) platform-as-a-service: here, a set of tools and services are provided for application development, deployment and monitoring without worrying about the underlying hardware. 3) software-as-a-service delivers application over the web to end-users.

- Dynamically configurable: Cloud resources are delivered through the web by easily manageable graphical interfaces and APIs. They empower cloud providers to provision services that users can configure dynamically and manage seamlessly.

Because of these features, cloud computing is increasingly used amidst researchers for scientific workflows to perform high throughput computing and data analysis [89]. Numerous disciplines such as astronomy, physics, biology, and others use scientific workflows to perform large scale complex analyses. Features like dynamic provisioning and innovative pricing models bring a new dimension for workflow scheduling, making it cost-effective and faster. However, using cloud computing for scheduling scientific workflows has some challenges and issues, which are outlined in our next section.

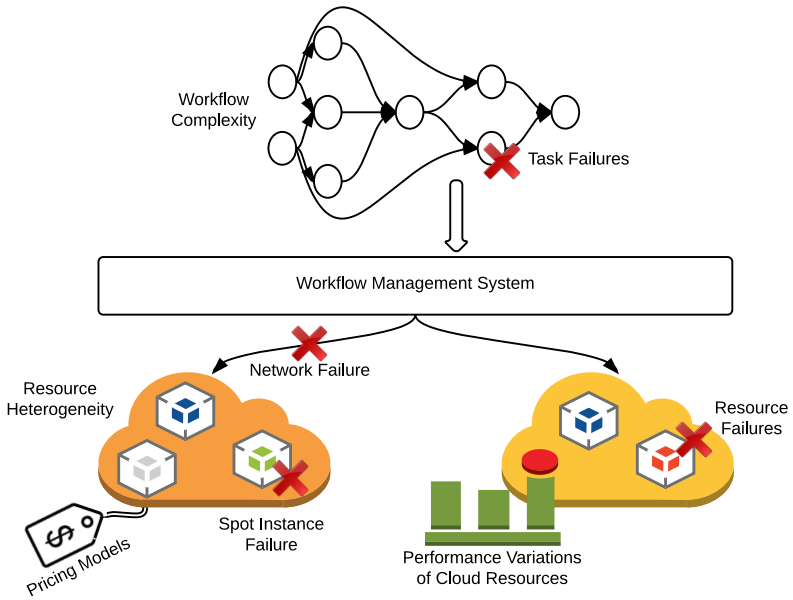


Figure 1.3: Research challenges in scheduling scientific workflows on cloud environments

1.2 Research Challenges and Objectives

Cloud computing offers virtualized servers, which are dynamically managed, monitored, maintained, and governed by market principles. As a subscription based computing service, it provides a convenient platform for *scientific workflows* due to features like application scalability, heterogeneous resources, dynamic resource provisioning, and a pay-as-you-go cost model.

However, these environments are prone to performance variations and different types of failures (e.g., in resources or in platforms) as illustrated in Figure 1.3. In particular, the likelihood of performance variation and failure increases for long-running workflows [101].

For instance, Dejun et al. [44] show that the behavior of multiple "identical" resources vary in performance while serving exactly the same workload. CPU and I/O performances also vary significantly for different identical instances. A performance variation of 4% to 16% is observed when cloud resources share network and disk I/O [10]. Additionally, VM start up and shutdown times of instances vary based on the operating system, instance type, pricing model, and location [94]. The performance variation of

VMs in clouds affects the overall execution time (i.e. makespan) of the workflow. It also increases the difficulty to estimate the task execution time accurately.

Failures also affect the overall workflow execution time by increasing its makespan. Failures in a workflow application are mainly of the following types: task failures, machine (VM) failures, and workflow-level failures [67]. Task failures may occur due to dynamic execution environment configurations, missing input data, or system errors. Machine (VM) failures are caused by hardware failures and load in a distributed system, among other reasons. Workflow level failures can occur due to factors such as machine failures or cloud outages.

Failures in a workflow environment can occur at different levels [110]: hardware, operating system, middleware, task, workflow, and user. Some of the prominent faults that occur are network failures, machine crashes, out-of-memory, file not found, authentication issues, file staging errors, uncaught exceptions, data movement issues, and user-defined exceptions. Gao et al. [57] identify that cloud systems are not fully protected systems and are prone to soft errors. Similarly, Ko et al. [80] mention that just in the period 2009 to 2011, 172 unique outages occurred among various cloud providers. At the scale of cloud computing, these errors could potentially worsen application performance.

Added to this, cloud providers like Amazon sell data center capacity that is idle or unused as spot instances [2] (SI). Users compete in an auction-like market where they bid a maximum price for these SIs they are willing to pay. The user is provided the instance whenever the spot price is lower than their bid [136]. However, when the user bid goes below the spot price, Amazon terminates the resources, such failures are called out-of-bid failures. Cloud users using SIs to reduce costs must employ strategies to address these out-of-bid failures [112]. These out-of-bid failures introduce a new dimension to failures, here failures are proportional to the value of the bid price. These failures are dependent on the budget an application is willing to spent. Research has shown that these instances provide huge cost benefits and for that an effective bidding strategy is essential. These innovative pricing models come with different SLAs that applications need to address.

Cloud resources comes with a variety of configuration characteristics, with different

[2] http://aws.amazon.com/ec2/purchasing-options/spot-instances/

cpu cores, memory, storage and others. The execution times of tasks vary on these resource, the ability to choose the right resource depending on the deadline and budget of the workflow is a research challenge. How to address the heterogeneity amidst resources for an application depending on this deadline and budgetary constraints is a valuable question that needs to be answered.

Lastly, workflows are generally composed of thousands of tasks, with complicated dependencies between the tasks. These tasks are interdependent with various execution times. Scheduling these workflow tasks onto heterogeneous VMs is an NP-Complete problem [73]. Therefore, necessity for fault-tolerance arises from the complexity of the application and environment. Workflows are applications that are most often used in a collaborative environment spread across the geography involving various people from different domains (e.g., [74]). So much diversity is a potential cause for adversities. Hence, to provide a seamless experience over a distributed environment for multiple users of a complex application, fault-tolerance is a paramount requirement of any WFMS.

This thesis provides effective solutions arising from these research challenges by answering the following fundamental question:

How does one make workflow scheduling algorithms robust and fault-tolerant for cloud computing environments?

1.3 Methodology

This thesis employs two main methodologies to evaluate the proposed algorithms:

1. **Discrete-event simulation**: Workflow applications are complex with numerous jobs and multiple dependencies. Conducting large scale experiments on real cloud infrastructures is time consuming, costly and extremely difficult. Therefore, a discrete-event based simulator was employed to evaluate our algorithms. Discrete-event simulation enables us to conduct experiment and allows us to control various parameters and evaluate the heuristics under multiple scenarios effectively, economically, and swiftly. We use and extend CloudSim [21] to simulate the cloud

environment. The simulator was extended to support workflow applications, making it easy to define, deploy and schedule workflows. A failure event generator was also integrated into the CloudSim, which generates failures from an input failure trace.

2. **System Prototype**: A multi-cloud utility for a workflow management system was developed. A resource provisioning policy for such an environment was also proposed. The system was tested on two cloud infrastructures to run this experiment: a private cloud and a public cloud.

1.3.1 Spot Market Traces

This work has used real Amazon AWS EC2 spot market traces for our evaluation of chapter 4 and 5. The spot price history is taken from Amazon EC2 US West region (North California availability zone). The spot price history provides information of the spot price and time for a specific instance.

1.3.2 Failure Traces

For the experiment of Chapter 3, one of the failure models was simulated through failure traces. Due to lack of publicly available cloud specific failure traces, Condor (CAE) Grid failure dataset [147], available as a part of Failure Trace Archive [81] was chosen. This dataset was collected by the Condor team at the University of Wisconsin-Madison from the Compact Muon Solenoid (CMS) experiment at the European Organization for Nuclear Research (CERN) [72].

1.3.3 Workflow Applications

State-of-the art workflow applications were used to evaluate the heuristics. Five workflows (Montage, CyberShake, Epigenomics, LIGO and SIPHT) were considered. Their characteristics are explained in detail by Juve et al. [74]. These workflows cover all the

basic components such as pipeline, data aggregation, data distribution and data redistribution.

1.3.4 Case Study Application

The system prototype was evaluated with the montage application [16], which is a complex astronomy workflow. We have used a montage workflow consisting of 110 tasks, where the number of the tasks indicate the number of images used. It is an I/O intensive application, which produces a mosaic of astronomic images.

1.4 Contributions

This thesis proposes novel heuristic algorithms for robust and fault-tolerant workflow scheduling on cloud computing platforms. Additionally, we use the dynamic pricing models offered by cloud providers to minimize cost and time whilst providing fault-tolerant schedules. Specifically, the key findings and contributions of this thesis are:

1 **Novel Heuristic Algorithms**: Four novel fault-tolerant workflow scheduling heuristics are proposed in this thesis. These heuristics employ various fault-tolerant techniques to mitigate failures and performance variations experienced in the cloud.

   – Chapter 3 proposes a heuristic that uses slack time to make schedules robust against performance variations. The concept of slack time is detailed in Chapters 2 and 3. This algorithm remaps failed tasks and also employs checkpointing to save execution time.

   – Chapter 4 proposes a heuristic that uses both on-demand and spot instances to save executions cost. It also provides a heuristic that can mitigate spot instance out-of-bid failures by employing task retry and checkpointing. Results have shown that using spot instances reduces up to 70% execution costs.

   – The heuristic in Chapter 5, similar to the one in chapter 4, uses both on-demand and spot instances to save execution costs. The proposed heuristics

mitigate spot instance out-of-bid failures, additionally it also address VM failures and network failures by employing task retry and task replication.

– In Chapter 6, a heuristic that utilizes a multi-cloud framework to schedule resources based on budget constraints is proposed. Upon resource failures, this algorithms reschedules the failed task onto another resource.

In summary, we have demonstrated numerous heuristic algorithms that employ fault-tolerant techniques developed specifically for cloud environments, which address failures and performance variations experienced in the environment.

2 **Bidding Strategy**: Bidding strategies are proposed that aid workflow scheduling algorithms to effectively bid spot instances, such that failures and execution cost are minimized. The proposed Intelligent Bidding Strategy bids prices closer to the spot price in the beginning of the execution and gradually increases the bid price closer to the on-demand price as the workflow nears the completion based on the current spot price, on-demand price, time flag of the workflow, failure probability of the previous bid price, and the current time.

3 A **performance evaluation study on time, cost and fault-tolerance**. Each of the heuristics proposed are studied with respect to the execution time, cost and fault-tolerance. Results have demonstrated that our proposed algorithms are robust and fault-tolerant and can minimize cost and time. We have also studied the effect of spot price volatility on checkpointing and the results demonstrate that for low spot prices, frequent checkpointing is not profitable.

4 This thesis also proposes **two metrics to measure robustness and fault-tolerance** of a schedule. The first metric *robustness probability*, measures the likelihood of the workflow to finish before a given deadline. The second metric *tolerance time* is the amount of time a workflow schedule can be delayed, such that the deadline constraint is not violated.

5 **Multi-cloud resource plug-in**: Multiple cloud providers offer clouds resource in an attractive way. An application running in a multi-cloud environment can benefit

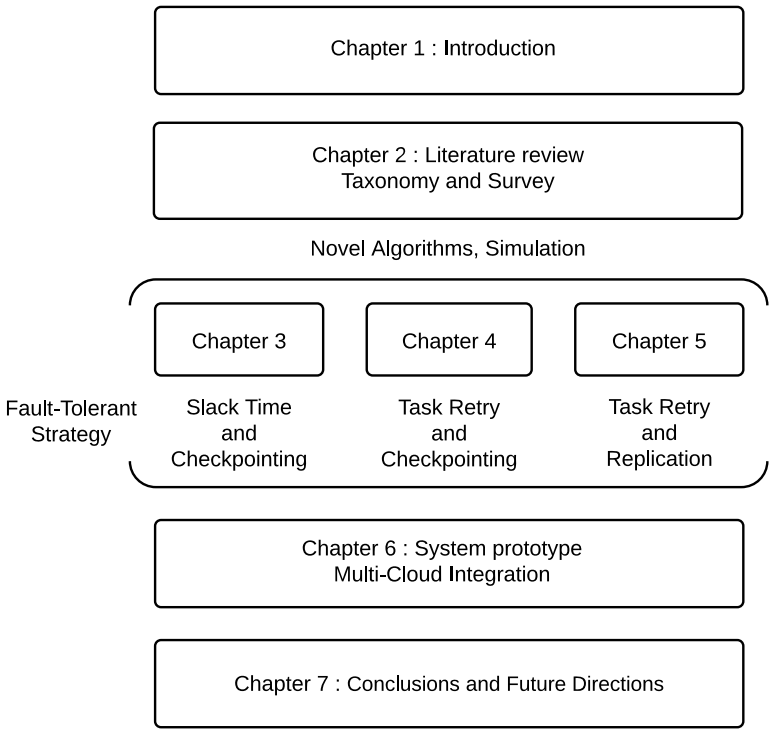


Figure 1.4: Thesis organization.

from pricing, wider resource types, and higher reliability to name a few.

As a part of the system prototype, we have integrated a multi-cloud framework to a workflow management system. This was demonstrated using an astronomy case study and mapping that workflow on private and public cloud infrastructures.

1.5 Thesis Organization

The thesis is structured as illustrated in Figure 1.4 into seven core chapters, and are derived from journal and conference papers published/submitted during the PhD candidature. An overview of the details of the thesis organization is presented here:

- Chapter 2 presents a Taxonomy of faults and fault-tolerant techniques, and a survey of the existing workflow management systems with respect to these taxonomies and the techniques. In addition, various failure models, metrics, tools, and support systems are also classified.

- Chapter 3 proposes a robust scheduling algorithm using checkpointing and slack time of resources, and resource allocation policies that schedule workflow tasks on heterogeneous cloud resources while trying to minimize the total elapsed time and the cost. The chapter is derived from:

  – **Poola D.**, Garg S.K., Buyya R., Yang Y., and Ramamohanarao K., Robust Scheduling of Scientific Workflows with Deadline and Budget Constraints in clouds, Proceedings of the 28th IEEE International Conference on Advanced Information Networking and Applications (AINA-2014), Victoria Canada.

- Chapter 4 proposes a scheduling algorithm that schedules tasks on cloud resources using two different pricing models (spot and on-demand instances) to reduce the cost of execution whilst meeting the workflow deadline. The proposed algorithm is fault tolerant against the premature termination of spot instances and also robust against performance variations of cloud resources. The algorithm proposed uses task retry and checkpointing techniques to achieve fault-tolerance. The chapter is derived from:

  – **Poola D.**, Ramamohanarao K., and Buyya R., Fault-Tolerant Workflow Scheduling Using Spot Instances on Clouds, Proceedings of the 13th International Conference on Computational Science (ICCS-2014), Cairns Australia.

- Chapter 5 presents an adaptive, just-in time scheduling algorithm for scientific workflows. This algorithm judiciously uses both task retry and task replication to provide fault-tolerance. The proposed scheduling algorithm also consolidates resources to minimize execution time and cost. The chapter is derived from:

  – **Poola D.**, Ramamohanarao K., and Buyya R., Enhancing Reliability of Workflow Execution Using Task Replication and Spot Instances, Accepted in the ACM Transactions on Autonomous and Adaptive Systems (TAAS), ISSN:1556-4665, ACM Press, New York, USA, 2015 (in press, accepted on Aug. 13, 2015).

- Chapter 6 presents a prototype system developed to provide a multi-cloud integration to the flagship project of the University of Melbourne, the cloudbus workflow

management system.

- Chapter 7 concludes this thesis with a summary of contributions, future research directions, and finals remarks.

Chapter 2
A Taxonomy and Survey

In recent years, workflows have emerged as an important abstraction for collaborative research and managing complex large-scale distributed data analytics. Workflows are increasingly becoming prevalent in various distributed environments, such as clusters, grids, and clouds. These environments provide complex infrastructures that aid workflows in scaling and parallel execution of their components. However, they are prone to performance variations and different types of failures. Thus, workflow management systems need to be robust against performance variations and tolerant against failures. Numerous research studies have investigated fault-tolerant aspect of the workflow management system in different distributed systems. In this study, we analyze these efforts and provide an in-depth taxonomy of them. We present the ontology of faults and fault-tolerant techniques then position the existing workflow management systems with respect to the taxonomies and the techniques. In addition, we classify various failure models, metrics, tools, and support systems. Finally, we identify and discuss the strengths and weaknesses of the current techniques and provide recommendations on future directions and open areas for the research community.

2.1 Introduction

WORKFLOWS orchestrate the relationships between dataflow and computational components by managing their inputs and outputs. In the recent years, scientific workflows have emerged as a paradigm for managing complex large scale distributed data analysis and scientific computation. Workflows automate computation, and thereby accelerate the pace of scientific progress easing the process for researchers.

In addition to automation, it is also extensively used for scientific reproducibility, result sharing and scientific collaboration among different individuals or organizations. Scientific workflows are deployed in diverse distributed environments, starting from supercomputers and clusters, to grids and currently cloud computing environments [61,75].

Distributed environments usually are large scale infrastructures that accelerate complex workflow computation; they also assist in scaling and parallel execution of the workflow components. The likelihood of failure increases specially for long-running workflows [101]. However, these environments are prone to performance variations and different types of failures. This demands the workflow management systems to be robust against performance variations and fault-tolerant against faults.

Over the years, many different techniques have evolved to make workflow scheduling fault-tolerant in different computing environments. This chapter aims to categorize and classify different fault-tolerant techniques and provide a broad view of fault-tolerance in workflow domain for distributed environments.

Workflow scheduling is a well studied research area. Yu et al. [148] provided a comprehensive view of workflows, different scheduling approaches, and different workflow management systems. However, this work did not throw much light on fault-tolerant techniques in workflows. Plankensteiner et al. [110] have recently studied different fault-tolerant techniques for grid workflows. Nonetheless, they do not provide a detailed view into different fault-tolerant strategies and their variants. More importantly, their work does not encompass other environments like clusters and clouds.

In this chapter, we aim to provide a comprehensive taxonomy of fault-tolerant workflow scheduling techniques in different existing distributed environments. We first start with an introduction to workflows and workflow scheduling. Then, we introduce fault-tolerance and its necessity. We provide an in-depth ontology of faults in section 2.4. Following which, different fault-tolerant workflow techniques are detailed. In section 2.6, we describe different approaches used to model failures and also give definition of various metrics used in literature to assess fault-tolerance. Finally, prominent workflow management systems are introduced and a description of relevant tools and support systems that are available for workflow development is provided.

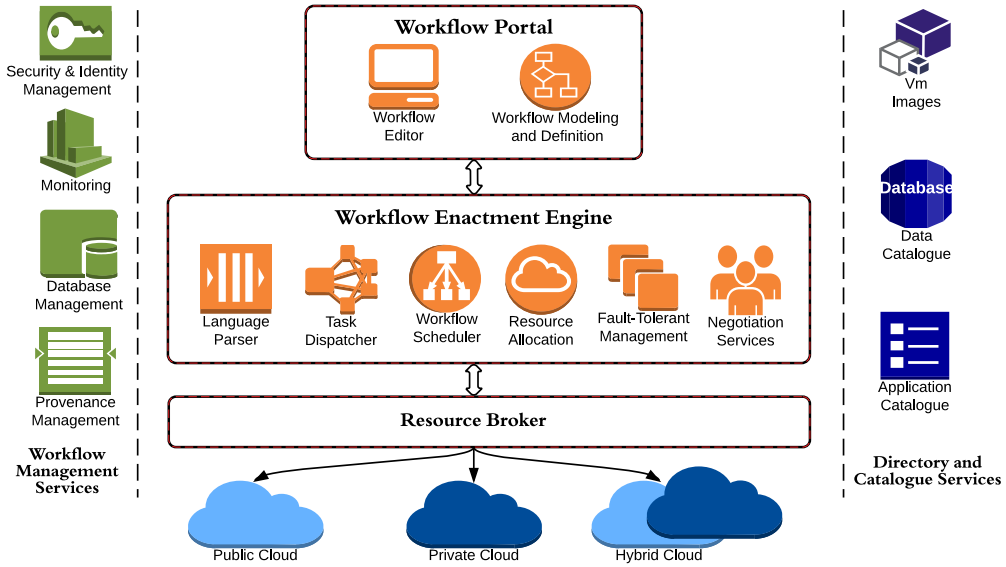


Figure 2.1: Architecture of cloud workflow management system. Portal, enactment engine, and resource broker form the core of the WFMS performing vital operations, such as designing, modeling, and resource allocation. To achieve these operations, the workflow management services (left column) provide security, monitoring, database, and provenance management services. In addition, the Directory and Catalogue services (right column) provide catalog and meta-data management for the workflow execution.

2.2 Background

2.2.1 Workflow Management Systems

Workflow management systems (WFMS) enable automated and seamless execution of workflows. They allow users to define and model workflows, set their deadline and budget limitations, and the environments in which they wish to execute. The WFMS then evaluates these inputs and executes them within the defined constraints.

The prominent components of a typical cloud WFMS is given in Figure 2.1. The *workflow portal* is used to model and define abstract workflows i.e., tasks and their dependencies. The *workflow enactment engine* takes the abstract workflows and parses them using a language parser. Then, the *task dispatcher* analyses the dependencies and dispatches the ready tasks to the scheduler. The *scheduler*, based on the defined scheduling algorithms schedules the workflow task onto a resource. We further discuss about workflow scheduling in the next section. Workflow enactment engine also handles the

fault-tolerance of the workflow. It also contains a resource allocation component which allocates resources to the tasks through the resource broker.

The *resource broker* interfaces with the infrastructure layer and provides a unified view to the enactment engine. The resource broker communicates with compute services to provide the desired resource.

The *directory and catalogue services* house information about data objects, the application and the compute resources. This information is used by the enactment engine, and the resource broker to make critical decisions.

Workflow management services, in general, provide important services that are essential for the working of a WFMS. *Security and identify* services ensure authentication and secure access to the WFMS. *Monitoring* tools constantly monitor vital components of the WFMS and raise alarms at appropriate times. *Database management* component provides a reliable storage for intermediate and final data results of the workflows. *Provenance management services* capture important information such as, dynamics of control flows and data, their progressions, execution information, file locations, input and output information, workflow structure, form, workflow evolution, and system information [141]. Provenance is essential for interpreting data, determining its quality and ownership, providing reproducible results, optimizing efficiency, troubleshooting and also to provide fault-tolerance [35,36].

2.2.2 Workflow Scheduling

As mentioned earlier, a workflow is a collection of tasks connected by control and/or data dependencies. Workflow structure indicates the temporal relationship between tasks. Workflows can be represented either in Directed Acyclic Graph (DAG) or non-DAG formats. In this thesis, workflows are represented in DAG formats (as shown in Figure 2.3), where the vertices represent task nodes and the directed edges represent control and/or data dependencies.

Scheduling maps workflow tasks on to distributed resources such that the dependencies are not violated. Workflow Scheduling is a well-known NP-Complete problem [73].

The workflow scheduling architecture specifies the placement of the scheduler in a

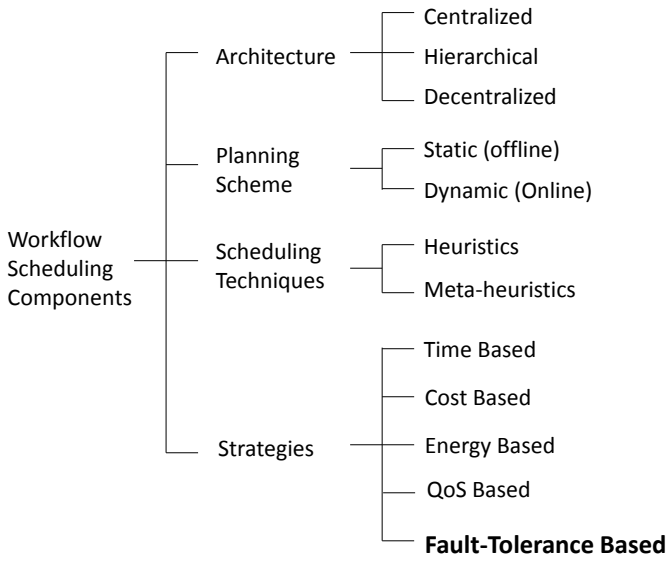


Figure 2.2: Components of workflow scheduling.

WFMS and it can be broadly categorized into three types as illustrated in Figure 2.2: *centralized*, *hierarchical*, and *decentralized* [148]. In the *centralized* approach, a centralized scheduler makes all the scheduling decisions for the entire workflow. The drawback of this approach is that it is not scalable; however, it can produce efficient schedules as the centralized scheduler has all the necessary information. In *hierarchical* scheduling, there is a central manager responsible for controlling the workflow execution and assigning the sub-workflows to low-level schedulers. The low-level schedulers map tasks of the sub-workflows assigned by the central manager. In contrast, *decentralized* scheduling has no central controller. It allows tasks to be scheduled by multiple schedulers, each scheduler communicates with each other and schedules a sub-workflow or a task [148].

Workflow schedule planning for workflow applications also known as planning scheme are of two types: *static(offline)* and *dynamic(online)*. *Static* scheme map tasks to resources at the compile time. These algorithms require the knowledge of workflow tasks and resource characteristics beforehand. On the contrary, *dynamic* scheme can make few assumptions before execution and make scheduling decision just-in-time [82]. Here, both dynamic and static information about environment is used in scheduling decisions.

Further, workflow scheduling techniques are the approaches or methodologies used to map workflow tasks to resources, and it can be classified into two types: *heuristics*

and *meta-heuristics*. *Heuristic* solutions exploit problem-dependent information to provide an approximate solution trading optimality, completeness, accuracy, and/or processing speed. It is generally used when finding a solution through exhaustive search is impractical. It can be further classified into list based scheduling, cluster based scheduling, and duplication based algorithms [124, 149]. On the other hand, *meta-heuristics* are more abstract procedures that can be applied to a variety of problems. A meta-heuristic approach is problem-independent and treats problems like black boxes. Some of the prominent meta-heuristic approaches are genetic algorithms, particle swarm optimization, simulated annealing, and ant colony optimization.

Each scheduling algorithm for any workflow have one or many objectives. The most prominent strategies or objectives used are given in Figure 2.2. Time, cost, energy, QoS, and fault-tolerance are most commonly used objectives for a workflow scheduling algorithm. Algorithms can have a single objective or multiple objectives based on the scenario and the problem statement. The rest of the chapter is focused on scheduling algorithms and workflow management systems whose objective is fault-tolerance.

2.3 Introduction to Fault-Tolerance

Failure is defined as any deviation of a component of the system from its intended functionality. Resource failures are not the only reason for the system to be unpredictable, factors such as, design faults, performance variations in resources, unavailable files, and data staging issues can be few of the many reasons for unpredictable behaviors.

Developing systems that tolerate these unpredictable behaviors and provide users with seamless experience is the aim of fault-tolerant systems. Fault tolerance is to provide correct and continuous operation albeit faulty components. Fault-tolerance, robustness, reliability, resilience and Quality of Service (QoS) are some of the ambiguous terms used for this. These terminologies are used interchangeably in many works. Significant works have been carried out in this area encompassing numerous fields like job-shop scheduling [85], supply chain [65], and distributed systems [124, 128].

Any fault-tolerant WFMS need to address three important questions [128]: (a) what

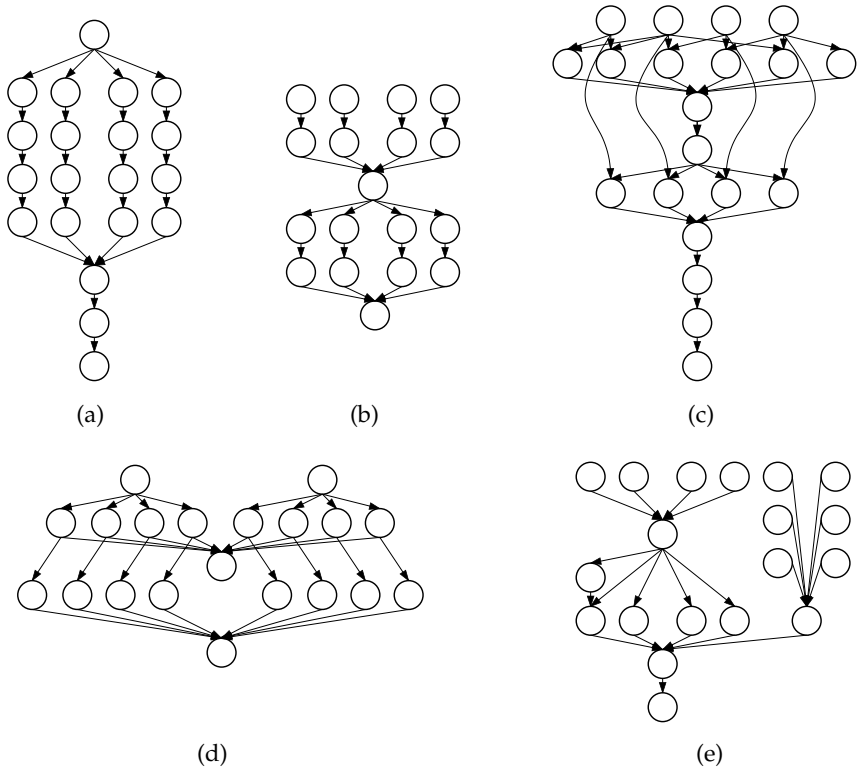


Figure 2.3: Examples of the state-of-the-art workflows [74]: (a) Epigenomics: DNA sequence data obtained from the genetic analysis process is split into several chunks and are used to map the epigenetic state of human cells. (b) LIGO: detects gravitational waves of cosmic origin by observing stars and black holes. (c) Montage: creates a mosaic of the sky from several input images. (d) CyberShake: uses the Probabilistic Seismic Hazard Analysis (PSHA) technique to characterize earth-quake hazards in a region. (e) SIPHT: searches for small un-translated RNAs encoding genes for all of the bacterial replicas in the NCBI database.

are the factors or uncertainties that the system is fault-tolerant towards? (b) What behavior makes the system fault-tolerant? (c) How to quantify the fault-tolerance i.e., what is the metric used to measure fault-tolerance?

In this survey we categorize and define the taxonomy of various types of faults that a WFMS in a distributed environment can experience. We further develop ontology of different fault-tolerant mechanisms that are used until now. Finally we provide numerous metrics that measure fault-tolerance of a particular scheduling algorithm.

2.3.1 Necessity for Fault-Tolerance in Distributed Systems

Workflows, generally, are composed of thousands of tasks, with complicated dependencies between the tasks. For example, some prominent workflows (as shown in Figure 2.3) widely considered are Montage, CyberShake, Broadband, Epigenomics, LIGO Inspiral Analysis, and SIPHT, which are complex scientific workflows from different domains such as astronomy, life sciences, physics and biology. These workflows are composed of thousands of tasks with various execution times, which are interdependent.

Workflow tasks are often executed on distributed resources that are heterogeneous in nature. WFMSs that allocates these workflows uses middleware tools that require to operate congenially in a distributed environment. This very complex and complicated nature of WFMSs and its environment invite numerous uncertainties and chances of failures at various levels.

In particular, in data-intensive workflows that continuously process data, machine failure is inevitable. Thus, failure is a major concern during the execution of data-intensive workflows frameworks, such as MapReduce and Dryad [69]. Both transient (i.e., fail-recovery) and permanent (i.e., fail-stop) failures can occur in data-intensive workflows [79]. For instance, Google reported on average 5 permanent failures in form of machine crashes per MapReduce workflow during March 2006 [37] and at least one disk failure in every run of MapReduce workflow with 4000 tasks.

Necessity for fault-tolerance arises from this very nature of the application and environment. Workflows are applications that are most often used in a collaborative environment are spread across the geography involving various people from different domains (e.g., [74]). So many diversities are potential causes for adversities. Hence, to provide a seamless experience over a distributed environment for multiple users of a complex application, fault-tolerance is a paramount requirement of any WFMS.

2.4 Taxonomy of Faults

Fault is defined as a defect at the lowest level of abstraction. A change in a system state due to a fault is termed as an error. An error can lead to a failure, which is a deviation

of the system from its specified behavior [59,70]. Before we discuss about fault-tolerant strategies it is important to understand the fault-detection and identification methodologies and the taxonomy of faults.

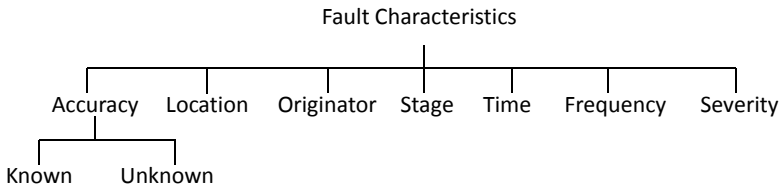


Figure 2.4: Elements through which faults can be characterized.

Faults can be characterized in an environment through various elements and means. Lackovic et al. [83] provide a detailed list of these element that are illustrated in Figure 2.4. *Accuracy* of fault detection can be either known or unknown faults. Known faults are those which have been reported before and solutions for such faults are known. *Location* is the part of the environment where the fault occurs. *Originator* is the part of the environment responsible for the fault to occur. *Stage* of the fault refers to the phase of the workflow lifecycle (design, build, testing, and production) when the fault occurred. *Time* is the incidence time in the execution when the fault happened. *Frequency*, as the name suggests identifies the frequency of fault occurrence. *Severity* specifies the difficulty in taking the corrective measures and details the impact of a particular fault. More details of these elements can be found in [83].

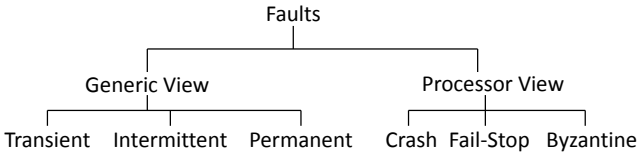


Figure 2.5: Faults: views and their classifications.

At a high level, faults can be viewed in two different ways, *generic view*, and the *processor view*. The *generic view* of faults can be classified into three major types as shown in Figure 2.5: *transient*, *intermittent* and *permanent* [83]. *Transient* faults invalidate only the current task execution, on a rerun or restart these fault most likely will not manifest again [13]. *Intermittent* faults appear at infrequent intervals. Finally, *permanent* faults are faults whose defects cannot be reversed.

From a *processor's perspective*, faults can be classified into three classes: *crash*, *fail-stop*, and *byzantine* [59]. This is mostly used for resource or machine failures. In the *crash* failure model, the processor stops executing suddenly at a specific point. In *fail-stop* processors internal state is assumed to be volatile. The contents are lost when a failure occurs and it cannot be recovered. However, this class of failure does not perform an erroneous state change due to a failure [122]. *Byzantine* faults originate due to random malfunctions like aging or external damage to the infrastructure. These faults can be traced to any processor or messages [32].

Faults in a workflow environment can occur at different levels of abstraction [110]: hardware, operating system, middleware, task, workflow, and user. Some of the prominent faults that occur are network failures, machine crashes, out-of-memory, file not found, authentication issues, file staging errors, uncaught exceptions, data movement issues, and user-defined exceptions. Plankensteiner et al. [110] detail various faults and map them to different level of abstractions.

2.5 Taxonomy of Fault-Tolerant Scheduling Algorithms

This section details the workings of various fault-tolerant techniques used in WFMS. In the rest of this section, each technique is analyzed and their respective taxonomies are provided. Additionally, prominent works using each of these techniques are explained. Figure 2.6 provides an overview of various techniques that are used to provide fault-tolerance.

2.5.1 Replication

Redundancy in space is one of the widely used mechanisms for providing fault-tolerance. Redundancy in space means providing additional resources to execute the same task to provide resilience and it is achieved by duplication or replication of resources. There are broadly two variants of redundancy of space, namely, task duplication and data replication.

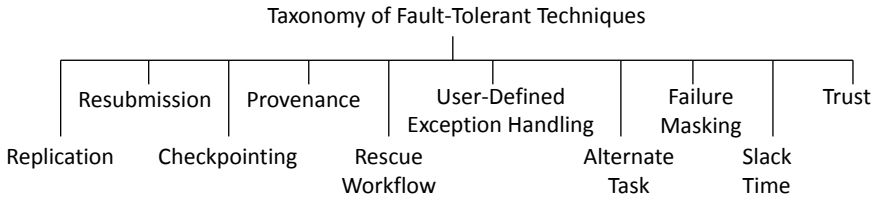


Figure 2.6: Taxonomy of workflow scheduling techniques to provide fault-tolerance.

Task Duplication

Task duplication creates replica of tasks. Replication of tasks can be done concurrently [31], where all the replicas of a particular task start executing simultaneously. When tasks are replicated concurrently, the child tasks start its execution depending on the schedule type. Figure 2.7 illustrates the taxonomy of task duplication.

Schedules types, are either *strict* or *lenient*. In *strict* schedule the child task executes only when all the replicas have finished execution [12]. In the *lenient* schedule type, the child tasks start execution as soon as one of the replicas finishes execution [31].

Replication of task can also be performed in a backup mode, where the replicated task is activated when the primary tasks fail [100]. This technique is similar to retry or redundancy in time. However, here, they employ a backup overloading technique, which schedules the backups for multiple tasks in the same time period to effectively utilize the processor time.

Duplication is employed to achieve multiple objectives, the most common being fault-tolerance [12, 64, 78, 155]. When one task fails, the redundant task helps in completion of the execution. Additionally, algorithms employ data duplication where data is replicated and pre-staged, thereby moving data near computation especially in data intensive workflows to improve performance and reliability [28]. Furthermore, estimating task execution time a priori in a distributed environment is arduous. Replicas are used to circumvent this issue using the result of the earliest completed replica. This minimizes the schedule length to achieve hard deadlines [33, 45, 114, 132], as it is effective in handling performance variations [31]. Calheiros et al. [20] replicated tasks in idle time slots to reduce the schedule length. These replicas also increase resource utilization without any extra cost.

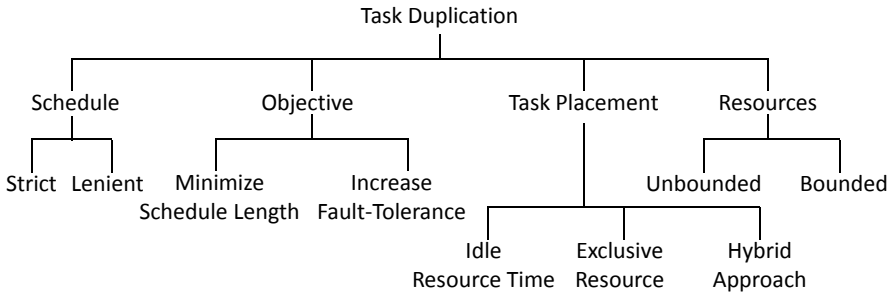


Figure 2.7: Different aspects of task duplication technique in providing fault-tolerance.

Task duplication is achieved by replicating tasks in either *idle cycles* of the resources or *exclusively on new resources*. Some schedules use a *hybrid approach* replicating tasks in both idle cycles and new resources [20]. Idle cycles are those time slots in the resource usage period where the resources are unused by the application. Schedules that replicate in these idle cycles profile resources to find unused time slot, and replicate tasks in those slots. This approach achieves benefits of task duplication and simultaneously considers monetary costs. In most cases, however, these idle slots might not be sufficient to achieve the needed objective. Hence, task duplication algorithms commonly place their task replicas on new resources. These algorithms trade off resource costs to their objectives.

There is a significant body of work in this area encompassing platforms like clusters, grids, and clouds [12, 18, 33, 45, 64, 78, 114, 132, 155]. Resources considered can either be *bounded* or *unbounded* depending on the platform and the technique. Algorithms with bounded resources consider a limited set of resources. Similarly, an unlimited number of resources are assumed in an unbounded system environment. Resource types used can either be *homogeneous* or *heterogeneous* in nature. *homogeneous* resources have similar characteristics, and *heterogeneous* resources on the contrary vary in their characteristics such as, processing speed, CPU cores, memory and etc. Darbha et al. [33] is one of the early works, which presents an enhanced search and duplication based scheduling algorithm (SDBS) that takes into account the variable task execution time. They consider a distributed system with homogeneous resources and assume an unbounded number of processors in their system.

Data Replication

Data in workflows are either not replicated (and are stored locally by the processing machines) or is stored on the distributed file system (DFS) where it is automatically replicated (e.g., in Hadoop Distributed File System (HDFS)). Although the former approach is efficient, particularly in data-intensive workflows, it is not fault-tolerant. That is, failure of a server storing data causes the re-execution of the affected tasks. On the other hand, the latter approach offers more fault tolerance but is not efficient due to significant network overhead and increasing the execution time of the workflow.

Hadoop, is a platform for executing data-intensive workflows, uses a static replication strategy for fault-tolerance. That is, users can manually determine the number of replicas that have to be created from the data. Such static and blind replication approach imposes a significant storage overhead to the underlying system (e.g., cluster or cloud) and slows down the execution of the MapReduce workflow. One approach to cope with this problem is to adjust the replication rate dynamically based on the usage rate of the data. This will reduce the storage and processing cost of the resources [152]. Cost-effective incremental replication (CIR) [88] is a strategy for cloud based workflows that predicts when a workflow is needed to replicate to ensure the reliability requirement of the workflow execution.

There are four major data-replication methods for data-intensive workflows on large-scale distributed systems (e.g., clouds) namely, *synchronous* and *asynchronous* replication, *rack-level* replication, and *selective* replication. These replication methods can be applied on input, intermediate, or output data of a workflow.

In *synchronous* data replication, such as those in HDFS, writers (i.e., producer tasks in a workflow) are blocked until replication finishes. Synchronous replication method leads to a high consistency because if a writer of block A returns, all the replicas of block A are guaranteed to be identical and any reader (i.e., consumer tasks in a workflow) of block A can read any replica. Nonetheless, the drawback of this approach is that the performance of writers might get affected as they have to be blocked. In contrast, *asynchronous* data replication [79] allows writers to proceed without waiting for a replication to complete. The asynchronous data replication consistency is not as accurate as the syn-

chronous method because even if a writer of block A returns, a replica of block A may still be in the replication process. Nonetheless, performance of the writers improves due to the non-blocking nature. For instance, with an asynchronous replication in Hadoop, Map and Reduce tasks can proceed without being blocked.

Rack-level data replication method enforces replication of the data blocks on the same rack in a data center. In cloud data centers, machines are organized in racks with a hierarchical network topology. A two-level architecture with a switch for each rack and a core switch is a common network architecture in these data centers. In this network topology the core switch can become bottleneck as it is shared by many racks and machines. That is, there is heterogeneity in network bandwidth where inter-rack bandwidth is scarce compared to intra-rack bandwidth. One example of bandwidth bottleneck is in the Shuffling phase of MapReduce. In this case, as the communication pattern between machines is all-to-all, the core switches become over-utilized whereas rack-level switches are underutilized. Rack-level replication reduces the traffic transferred through the bandwidth-scarce core switch. However, the drawback of the rack-level replication approach is that it cannot tolerate rack-level failures and if a rack fails, all the replicas become unavailable. There are observations that show rack-level failures are infrequent which proves the efficacy of rack-level replication. For instance, one study shows that Google experiences approximately 20 rack failures within a year [38].

Selective data replication is an approach where the data generated by the previous step of the workflow are replicated on the machine, where the failed task will be re-executed. For instance, in a chained MapReduce workflow, once there is a machine failure at the Map phase, the affected Map tasks can be restarted instantly, if the intermediate data generated by the previous Reduce tasks were replicated locally on the machine, where the failed Map task will be re-run. In this manner, the amount of intermediate data that needs to be replicated in the Map phase is reduced remarkably. However, it is not very effective for Reduce phase, because Reduce data are mostly locally consumed.

ISS [79] is a system that extends the APIs of HDFS and implements a combination of three aforementioned replication approaches. It implements a rack-level replication that asynchronously replicates locally-consumed data. The focus of ISS is on the management

of intermediate data in Hadoop data-intensive workflows. It takes care of all aspects of managing intermediate data such as writing, reading, Shuffling, and replicating. Therefore, a programming framework that utilizes ISS does not need to consider Shuffling. ISS transparently transfers intermediate data from writers (e.g., Map tasks) to readers (e.g., Reduce tasks).

As mentioned earlier, replicating input data or intermediate data on stable external storage systems (e.g., distributed file systems) is expensive for data-intensive workflows. The overhead is due to data replication, disk I/O, network bandwidth, and serialization which can potentially dominate the workflow execution time [153]. To avoid these overheads, in frameworks such as Pregel [93], which is a system for iterative graph computation, intermediate data are maintained in memory. Resilient Distributed Datasets (RDDs) [153] are distributed memory abstractions that enable data reuse in a fault-tolerant manner. RDDs are parallel data structures that enable users to persist intermediate data in memory and manipulate them using various operators. It also controls the partitioning of the data to optimize data placement. RDD has been implemented within the Spark [154] framework.

2.5.2 Resubmission

Resubmission tries to re-execute components to mitigate failures. Resubmission or redundancy in time helps recover from transient faults or soft errors. Resubmission is employed as an effective fault-tolerant mechanism by around 80% of the WFMSs [110]. Li et al. [86] claim that 41% of failures are recovered in their work through resubmission. Some of the WFMS that support resubmission for fault-tolerance are Askalon, Chemomentum, GWES, Pegasus, P-Grade, Proactive, Triana, Unicore [110].

Resubmission can be classified into two levels: *workflow* and *task* resubmission as illustrated in Figure 2.8. In workflow resubmission, as the name suggests, the entire application or a partial workflow is resubmitted [15].

Task resubmission, retries the same task to mitigate failure. Task retry/resubmission can be either done on the same resource or another resource [110]. Resubmission on the same resource is applicable when a task fails due to a transient failure or due to file

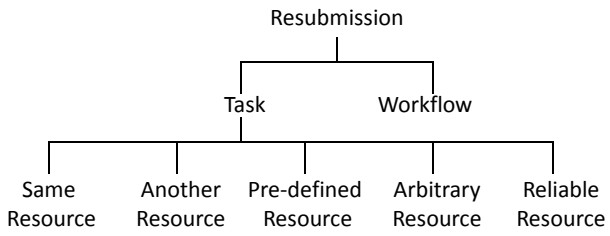


Figure 2.8: Taxonomy of resubmission fault-tolerant technique.

staging issues. In other cases this might not be the best approach to mitigate failures. Resubmission of the task can be either done on a fixed predefined resource [67] or on an arbitrary resource or a resource with high reliability. A fixed predefined resource is not necessarily the same resource, but the drawbacks are similar to that. Selecting a resource arbitrarily without a strategy is not the most effective solution to avoid failures. Employing a strategy whilst selecting resources, like choosing resources with high reliability, increases the probability of addressing failures. Zhang et al. [155] rank resources based on a metric called reliability prediction and use this metric to schedule their task retries.

Resources considered can either be homogeneous or heterogeneous in nature. In a heterogeneous resource type environment, different resource selection strategies have different impact on cost and time. A dynamic algorithm must take into consideration deadline and budget restrictions, and select resources that provide fault-tolerance based on these constraints. Clouds providers like Amazon, offer resources in an auction-like mechanism for low cost with low SLAs called spot instances. Poola et al. [112] have proposed a just-in-time dynamic algorithm that uses these low cost instances to provide fault-tolerant schedules considering the deadline constraint. They resubmit tasks upon failures to either spot or on-demand instances based on the criticality of the workflow deadline. This algorithm is shown to provide fault-tolerant schedule whilst reducing costs.

Algorithms usually have a predefined limit for the number of retries that they will attempt [42, 155] to resolve a failure. Some algorithms also have a time interval in addition to the number of retries threshold [67]. However, there are algorithms that consider infinite retries as they assume the faults to be transient in nature [26].

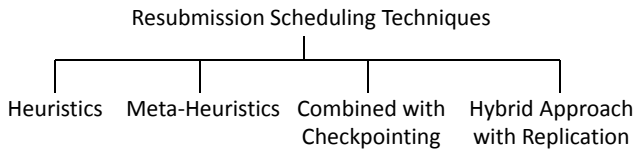


Figure 2.9: Different approaches used in resubmission algorithms.

Algorithms using resubmission can be broadly classified into four types as shown in Figure 2.9: *Heuristic* based [67,86,151], *meta-heuristic* based [15], *hybrid of resubmission and checkpointing* [155], and *hybrid of resubmission and replication* [109]. Heuristic based approaches are proven to be highly effective, although these solutions are often are based on a lot of assumptions and specific to a particular use case. Meta-heuristics provide near optimal solutions and are more generic approaches; however, they are usually time and memory consuming. Hybrid approaches with checkpointing saves time, do not perform redundant computing, and does not over utilize resources, when compared with replication or resubmission. However, these approaches delay the makespan as resubmission retries a task in case of failures, although, checkpointing reruns from a saved state it still requires additional time delaying the makespan. Replication with redundant approaches waste resources but do not delay the makespan as the replicas eliminates the necessity of rerunning a task.

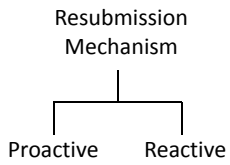


Figure 2.10: Classification of resubmission mechanisms.

Finally, resubmission fault-tolerant mechanisms are employed in two major ways (Figure 2.10): *proactive* and *reactive*. In the *proactive* mechanism [15, 116], the algorithm predicts a failure or a performance slowdown of a machine and reschedules it on another resource to avoid delays or failures. In *reactive* mechanism, the algorithms resubmit tasks or a workflow after a failure occurs.

Resubmission in workflow provides resilience for various faults. However, the drawback of this mechanism is the degradation in the total execution time when large number

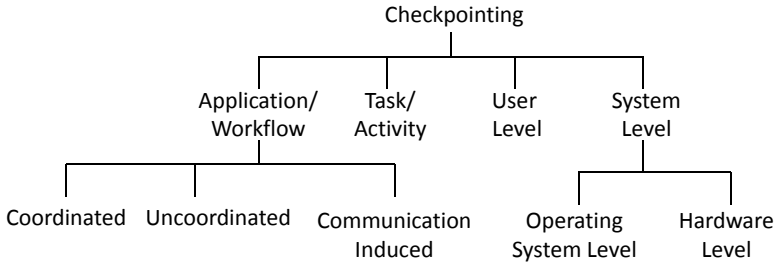


Figure 2.11: Taxonomy of checkpointing mechanism.

of failures occurs. Resubmission is ideal for an application during the execution phase and replication is well suited at the scheduling phase [109].

2.5.3 Checkpointing

Checkpointing is an effective and widely used fault-tolerant mechanism. In this process, states of the running process are periodically saved to a reliable storage. These saved states are called *checkpoints*. Checkpointing restores the saved state after a failure, i.e., the process will be restarted from its last checkpoint or the saved state. Depending on the host, we can restart the process on the same machine (if it has not failed) or on another machine [32, 53]. WFMS actively employ checkpointing as their fault-tolerant mechanism. More than 60% of these systems use checkpointing to provide resilience [110].

A checkpoint data file typically contains data, states and stack segments of the process. It also stores information of open files, pending signals and CPU states [48].

Checkpoint Selection Strategies

How often or when to take checkpoints is an important question while checkpointing. Various systems employ different checkpoint selection strategies. Prominent selection strategies are [25, 48, 51, 119]:

- event activity as a checkpoint.
- take checkpoints at the start and end time of an activity.
- take a checkpoint at the beginning and then after each decision activity.

- user defines some static stages during build-stage.
- take checkpoint when runtime completion duration is greater than maximum activity duration.
- take checkpoint when runtime completion duration is greater than mean duration of the activity.
- when an activity fails.
- when an important activity finishes completion.
- after a user defined deadline (e.g., percentage of workflow completion).
- underlying system changes like availability of services.
- application defined stages.
- based on linguistic constructs for intervention of programmers.

Issues and Challenges

Checkpointing provides fault-tolerance against transient faults only. If there is a design fault, checkpointing cannot help recover from it [49]. Another challenge here is to decide the number of checkpoints to be taken. As the frequency of checkpoints increases, the overhead also increases, whereas lower checkpoints leads to excessive loss of computation [134]. The overhead imposed by checkpointing depends on the level that it is applied (e.g., process or virtual machine level). A mathematical model is provided in [118] to calculate the checkpointing overhead of virtual machines.

In message-passing systems inter-process dependencies are introduced by messages. When one or more processes fail, these dependencies may lead to a restart even if the processes did not fail. This is called rollback propagation that may lead the system to the initial state. This situation is called domino effect [51]. Domino effect occurs if checkpoints are taken independently in an uncoordinated fashion in a system. This can be avoided by performing checkpoints in a coordinated manner. Further, if checkpoints are taken to maintain system-wide consistency then domino effect can be avoided [51].

Taxonomy of Checkpointing

As shown in Figure 2.11, there are four major checkpointing approaches: *Application/workflow-level*, *task/activity level*, *user level*, and *system level* implementation.

In *application/workflow-level* checkpointing implementation is usually performed within the source code, or is automatically injected into the code using external tools. It captures the state of the entire workflow and its intermediate data [48, 134]. This can be further classified into *coordinated*, *uncoordinated*, or *communication-induced* [51]. Coordinated approach takes checkpoints in a synchronized fashion to maintain a global state. Recovery in this approach is simple and domino effect is not experienced in this method. It maintains only one permanent checkpoint on a reliable storage, eliminating the need for garbage collection. The drawback is incurring a large latency in committing the output [51].

Coordinated checkpointing can further be achieved in the following ways: *Non-blocking* Checkpoint Coordination, Checkpointing with *Synchronized Clocks*, *Checkpointing and Communication Reliability*, and *Minimal Checkpoint Coordination*.

Non-Blocking Checkpoint Coordination: Here, the initiator takes a checkpoint and broadcasts a checkpoint request to all other activities. Each activity or task takes a checkpoint once it receives this checkpoint request and then further re-broadcasts the request to all tasks/activities.

Checkpointing with Synchronized Clocks: This approach is done with loosely synchronized clocks that trigger local checkpointing for all activities without an initiator.

Checkpointing and Communication Reliability: This protocol saves all the in-transit messages by their destination tasks. These messages need not be saved when communication channels are assumed to be unreliable.

Minimal Checkpoint Coordination: In this case, only a minimum subset of the tasks/activities is saved as checkpoints. The initiator identifies all activities with which it has communicated since the last checkpoint and sends them a request. Upon receiving the request, each activity further identifies other activities it has communicated since the last checkpoint and sends them a request.

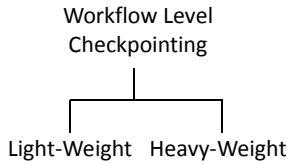


Figure 2.12: Workflow-level checkpointing.

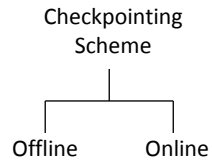


Figure 2.13: Checkpointing schemes.

Uncoordinated checkpointing allows each task to decide the frequency and time to save states. In this method, there is a possibility of a domino effect. As this approach is not synchronized, it may take many useless checkpoints that are not part of a global consistent state. This increases overhead and does not enhance the recovery process. Multiple uncoordinated checkpoints force garbage collection to be invoked periodically.

The last type of workflow-level checkpointing is *Communication-Induced Checkpointing*. In this protocol the information about checkpointing is piggybacked in the application messages. The receiver then uses this information to decide whether or not to checkpoint.

Based on the intermediate data, workflow-level checkpointing can also be subcategorized into two types: *Light-weight* and *Heavy-Weight* as illustrated in Figure 2.12. In *Light-weight* checkpointing the intermediate data is not stored, only a reference to it is stored assuming that the storage is reliable. Alternatively, *heavy-weight* checkpointing stores the intermediate data along with the required state information in a checkpoint [48, 134].

Task-level checkpointing saves the register, stack, memory, and intermediate states for every individual task running on a virtual machine [117] or a processor [48, 134]. When a failure occurs the task can restart from the intermediate saved state and this is especially important when the failures are independent. This helps recover individual units of the application.

User-level checkpointing uses a library to do checkpoints and the application programs are linked to it. This mechanism is not transparent as the applications are modified, recompiled and re-linked. The drawback being this approach cannot checkpoint certain shell scripts, system calls, and parallel application as the library may not be able access system files [49].

System-level checkpointing can be done either at the *operating system level* or the *hardware level*. This mechanism is transparent to the user and it does not necessarily modify the application program code. The problem with operating system level checkpointing is that it cannot be portable and modification at the kernel level is not always possible and difficult to achieve [49].

Performance Optimization

As discussed earlier, optimizing performance in a checkpoint operation is a challenge. The frequency of checkpoints impacts the storage and computation load. Checkpointing schemes can be broadly divided into *online* and *offline* checkpointing schemes as illustrated in Figure 2.13.

An *offline* checkpointing scheme determines the frequency for a task before its execution. The drawback being it is not an adaptive approach. On the other hand, *online* schemes determine the checkpointing interval dynamically based on the frequency of fault occurrences and the workflow deadline. Dynamic checkpointing is more adaptive and is able to optimize performance of the WFMS.

Checkpointing in WFMS

WFMSs employ checkpointing at various levels. At Workflow-level, two types of checkpointing can be employed Light-weight and Heavy-weight as stated earlier. Light-weight checkpointing is used by Chemomentum, GWEE, GWES, Pegasus, P-grade, and Traina WFMS. Similarly, heavy-weight checkpointing is employed by GWEE and GWES. Task-level checkpointing is employed by both Pegasus and P-Grade. Proactive WFMS checkpoints at the operating system level [110].

Kepler also checkpoints at the workflow layer [101], whereas, Karajan allows checkpointing the current state of the workflow at a global level. Here, timed or program-directed checkpoints can be taken, or checkpoints can be taken automatically at preconfigured time intervals, or it can be taken manually [139]. SwinDeW-C checkpoints using a minimum time redundancy based selection strategy [91].

2.5.4 Provenance

Provenance is defined as the process of metadata management. It describes the origins of data, the processes involved in its production, and the transformations it has undergone. Provenance can be associated with process(es) that aid data creation [127]. Provenance captures multiple important information like dynamics of control and data flows, their progressions, execution information, file locations, input and output information, workflow structure, form, workflow evolution, and system information [141]. Provenance is essential for interpreting data, determining its quality and ownership, providing reproducible results, optimizing efficiency, troubleshooting, and also to provide fault-tolerance [35, 36].

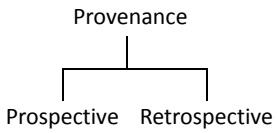


Figure 2.14: Forms of provenance.

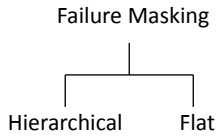


Figure 2.15: Forms of failure masking.

As detailed in Figure 2.14, provenance can be of two forms: *prospective* and *retrospective* [36]. *Prospective* provenance captures the specifications that need to be followed to generate a data product or class of data products. *Retrospective* provenance captures the executed steps similar to a detailed log of task execution. It also captures information about the execution environment used to derive a specific data product.

Provenance information is used to rerun workflows, these reruns can overcome transient system errors [126]. Provenance allows users to trace state transitions and detect the cause of inconsistencies. It is used to design recovery or undo paths from workflow fault states at the task granularity level. It is used as an effective tool to provide fault-tolerance in several WFMS.

2.5.5 Rescue Workflow

The rescue workflow technique ignores failed tasks and executes the rest of the workflow until no more forward progress can be made.

A rescue workflow description called rescue DAG containing statistical information

of the failed nodes is generated, which is used for later resubmission [148]. Rescue workflow technique is used by Askalon, Kepler and DAGMan [91,148].

2.5.6 User-Defined Exception Handling

In this fault-tolerant technique, users can specify a particular action or a predefined solution for certain task failures in a workflow. Such a technique is called user-defined exception handling [148]. This could also be used to define alternate tasks for predefined type of failures [67].

This mechanism is employed by Karajan, GWES, Proactive, and Kepler among the prominent WFMS [91,110].

2.5.7 Alternate Task

The alternate task fault-tolerant scheduling technique defines an alternative implementation of a particular task. When the predefined task fails, its alternative implementation is used for execution. This technique is particularly useful when two or more different implementations are available for a task. Each implementation has different execution characteristics but take the same input and produce same outputs. For example, there could be a task with two implementations, where one is less memory or compute intensive but unreliable, while the alternate implementation is memory intensive or compute intensive but more reliable. In such cases, the later implementation can be used as an alternative task.

This technique is also useful to semantically undo the effect of a failed task, that is, alternate tasks can be used to clean up the states and data of a partially executed failed task [67,148].

2.5.8 Failure Masking

Failure masking fault-tolerant technique ensures service availability, despite failures in tasks or resources [49]. This is typically achieved by redundancy, and in the event of

failure the services are provided by the active (i.e., surviving) tasks or resources masking failures. Masking can be of two forms: *hierarchical group masking* and *flat group masking*.

Hierarchical group masking uses a coordinator to monitor the redundant components and decides which copy should replace the failed component. The major drawback of this approach is the single point of failure of the coordinator.

Flat group masking resolves this single point of failure by being symmetric. That is, the redundant components are transparent and a voting process is used to select the replacement in adversity. This approach does not have a single point of failure, but imposes more overhead to the system.

2.5.9 Slack Time

Task slack time represents a time window within which the task can be delayed without extending the makespan. It is intuitively related to the robustness of the schedule. Slack time is computed as the minimum spare time on any path from the considered node to the exit node of the workflow. The formal definition of slack is given by Sakellariou and Zhao in [116].

Shi et al. [124] present a robust scheduling for heterogeneous resources using slack time to schedule tasks. They present a ϵ-constraint method where robustness is an objective and deadline is a constraint. This scheduling algorithm tries to find schedules with maximum slack time without exceeding the specified deadline. Similarly, Poola et al. [111] presented a heuristic considering heterogeneous cloud resources, they divided the workflow into partial critical paths, and based on the deadline and budget added slack time to these partial critical path's estimated execution time. Slack time added to the schedule enables the schedule time to tolerate performance variations and failures up to a certain extent, without violating the deadline.

2.5.10 Trust-Based Scheduling Algorithms

Distributed environments have uncertainties and are unreliable, added to this, some service providers may slightly violate SLAs (with respect to performance, startup or shutdown times) for many reasons including profitability. Therefore, WFMS typically

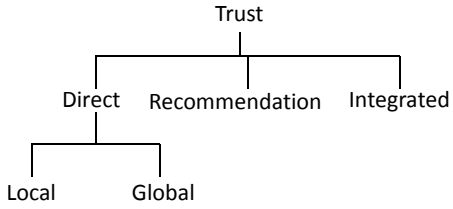


Figure 2.16: Methods for evaluating trust in trust-based algorithms used for fault-tolerant WFMS.

employ trust factor to make the schedule trustworthy. Trust is composed of many attributes including reliability, dependability, honesty, truthfulness, competence, and timeliness [142]. Including trust into workflow management significantly increases fault-tolerance and decreases failure probability of a schedule [142, 146].

Conventionally, trust models are of two types: *identity-based* and *behavior-based*. *Identity-based* trust model uses trust certificates to verify the reliabilities of components. *behavior-based* models observe and take the cumulative historical transaction behavior and also feedback of entities to evaluate the reliability [87].

Trust is evaluated by three major methods as shown in Figure 2.16: *Direct trust*, *Recommendation Trust*, and *Integrated Trust*. *Direct trust* is derived from the historical transaction between the user and the service. Here, no third party is used to evaluate the trust of the service [87]. Direct trust can be broadly of two types *local trust* and *global trust* [130]. *local trust* is computed based on a local system's transactions and similarly *global trust* is evaluated considering the entire global system's history. Yang et al. [146] use direct trust in their scheduling algorithm to decrease failure probability of task assignments and to improve the trustworthiness of the execution environment.

Recommendation trust is where the user consults a third party to quantify the trust of a service [87]. *Integration trust* is a combination of both direct and recommendation trust. This is usually done by a weighted approach [130]. Tan et al. [130] have proposed a reliable workflow scheduling algorithm using fuzzy technique. They propose an integrated trust metric combining direct trust and recommendation trust using a weighted approach.

Some of the drawbacks of trust models are: 1) majority of the trust models are designed for a particular environment under multiple assumptions. 2) trust is mostly stud-

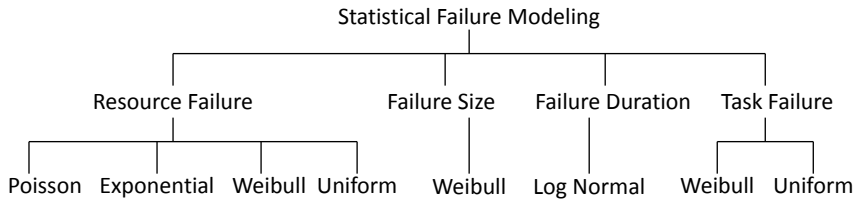


Figure 2.17: Distributions used for modeling failures for workflows in distributed environments.

ied in isolation without involving other system components [87].

2.6 Modeling of Failures in Workflow Management Systems

Failure models define failure rates, frequencies and other statistics observed in real systems, these models are used mainly in simulation and prediction systems to recreate failures. Failures can follow Poisson, Exponential, Weibull, Log normal, or uniform distributions, as illustrated in Figure 2.17. Failures can be independent or co-related. Benoit et al [14] model resource failure through Poisson distribution, they assume failures to be statistically independent and assume a constant failure rate for each processor. Chen and Deelman [26] also assume failure to be independent but use an exponential distribution and also use a non constant failure rate. Dongarra et al's. [46] work is similar to [26], but they assume constant failure rate for each processor.

Weibull distribution is widely used in failure modeling in different ways. Litke et al. [90] use Weibull distribution to estimate the failure probability of the next assigned task for a specific resource based on the estimated execution time of each task on the resource. Plankensteiner et al. [110] use a combination of distribution to model failures. They use Weibull distribution for mean time between failure (MTBF) for clusters and to model the size of failure. Further, they use Log-Normal distribution to estimate the duration of failure. Rahman et al. [113] use Weibull distribution in their simulation environment to determine whether a task execution will fail or succeed. If a task is likely to fail, they generate a random number from a uniform distribution and if that number is less than the failure probability of a resource at a particular grid, then the task is failed.

Distributions are used to evaluate reliability of tasks and resources. Wang et al. [143]

uses exponential distribution to evaluate task reliability based on real-time reputation. The reputation is defined by using their task failure rate.

All the above works consider failures to be independent. However, Javadi et al. [70] consider failures to be spatial and temporally correlated. Spatial correlations of failures imply that multiple failures occur on various nodes with a specified time interval. Temporal correlation denotes skewness in failures over time. They use spherical covariance model to determine temporal failure correlation and Weibull distribution for failure modeling.

2.7 Metrics Used to Quantify Fault-Tolerance

There are various metrics to measure the robustness or fault-tolerance of a workflow schedule. Each metric measures a different aspect and reports the schedule robustness based on certain constraints and assumptions. We present some prominent metrics used in the literature. The makespan considered in most cases is the actual makespan and not the predicted makespan.

Makespan Standard Deviation: It reports the standard deviation of the makespan. Narrower the distribution, better the schedule [23].

Makespan differential Entropy: Measures the differential entropy of the distribution, if the uncertainty is less, then the schedule is more robust [17].

Mean slack: Amount of time the task can be delayed without delaying the schedule is called task slack time. The slack of a schedule is the summation of slack times of all the tasks. Hence, more the slack in a schedule means more failures it can tolerate. Therefore, the schedule is more robust [17].

Probabilistic metric: Defines the makespan probability within two bounds. If the probability is high, then the robustness is high. This is because higher probability indicates that the makespan is close to the average makespan [123].

Lateness likelihood: A schedule is late if the makespan exceeds a given deadline. This metric gives the probability of the schedule to be late. If the lateness likelihood is high, the robustness of the schedule is low [124].

Reliability: Reliability of a compute service during a given time is defined as per the equation 2.1,

$$Reliability = (1 - (numFailure/n)) * mttf, \tag{2.1}$$

where, $numFailure$ is the number of failures experiences by the users, n is the number of users, and $mttf$ is the promised mean time to failure [58].

Workflow Failure Ratio: It is the percentage of failed workflows due to one or more task failures [6].

Request Rejection Ratio: It is the ratio of number of rejected requests to the total requests [6].

Workflow Success Probability: The success probability of the entire workflow is given as a product of the success probabilities of individual tasks [155].

Standard Length Ratio: It indicates the performance of the workflow. It is the ratio of turnaround time to the critical path time including the communication time between tasks. Turnaround time is the workflows' running time. Lower value of this metric signifies better performance [155].

Trust: This metric presents the trustworthiness of a particular resource. It is given by the following equation

$$Trust(S_i) = w_i * DT(S_i) + (1 - w_i) * RT(S_i), \tag{2.2}$$

where, $DT(S_i)$ is the direct trust based on historical experiences of the i^{th} service, $RT(S_i)$ is the recommendation trust by other users and w_i is the weight of $DT(S_i)$ and $RT(S_i)$ for the i^{th} service [130].

Failure probability (R_p): It is the likelihood of the workflow to finish before the given deadline [111, 124], which can be formulated as below:

$$R_p = (TotalRun - FailedRun)/(TotalRun), \tag{2.3}$$

where $TotalRun$ is number of times the experiment was conducted and $FailedRun$ is number of times the constraint, $finish_{t_n} \leqslant D$ was violated. Here, D is the deadline of the workflow and $finish_{t_n}$ is the workflow elapsed time.

Tolerance time (R_t): It is the amount of time a workflow can be delayed without violating the deadline constraint. This provides an intuitive measurement of robustness given the same schedule and resource to task mapping, expressing the amount of uncertainties it can further withstand. It is given by the Equation 2.4

$$R_t = D - finish_{t_n}. \tag{2.4}$$

2.8 Survey of Workflow Management Systems and Frameworks

This section provides a detailed view of the state-of-the-art WFMSs and also provide information about the different fault-tolerant techniques used, as described in section 2.5. These WFMSs are summarized in Table 2.1.

2.8.1 Askalon

Askalon [53] is a WFMS developed at the University of Innsbruck, Austria. It facilitates the development and optimization of applications on grid computing environments [53, 148]. The system architecture consists of the following components: 1) *Scheduler*: maps single or multiple workflows tasks onto the grid; 2)*Enactment Engine*: ensures reliable and fault-tolerant execution of applications; 3)*Resource Manager*: is responsible for negotiation, reservation, allocation of resources and automatic deployment of services. It also shields the user from low-level grid middleware technology; 4) *Performance Analysis*: supports automatic instrumentation and bottleneck detection (e.g., excessive synchronization, communication, load imbalance, inefficiency, or non scalability) within the grid; 5) *Performance Prediction service*: estimates execution times of workflow activities through a training phase and statistical methods based on a combination of historical data obtained from the training phase and analytical models [53, 54].

Askalon uses an xml-based workflow language called AGWL for workflow orchestration. It can be used to specify DAG-constructs, parallel loops and conditional statements such as switch and if/then/else. AGWL can express sequence, parallelism choice and

Table 2.1: Features, provenance information and fault-tolerant strategies of workflow management systems

WFMS	Features	Provenance	Fault-tolerant Strategy
Askalon University of Innsbruck , Austria. `http://www.dps.uibk.ac.at/projects/askalon/`	• Service Oriented Architecture • Single Access User Portal • UML Workflow Editor • X509 certificates support • Amazon EC2 API support • Grids and clouds	N/A	Resubmission, replication, checkpointing/restart, migration, user-defined exception, rescue workflow.
Pegasus USC Information Sciences Institute and the University of Wisconsin Madison. `http://pegasus.isi.edu/`	• Portability / Reuse • Performance and reliability • Scalability • Provenance • Data Management • Desktops, clusters, grids, and clouds	Keeps track of data locations, data results, and software used with its parameters.	Task Resubmission, Workflow Resubmission, workflow-level checkpointing, alternative data sources, rescue workflow.
Triana Cardiff University, United Kingdom.	• Modular java workflow environment • Job queuing • Comprehensive toolbox libraries • Grids and clouds	N/A	Light-weight checkpointing and restart of services are supported at the workflow level. Resubmissions are supported at the task level by the workflow engine, and alternate task technique is also employed.
Unicore 6 Collaboration between German research institutions and industries.	• Support for virtual organizations, X.509 certificates • Improved data management through DataFinder • Supports foreach loops and iteration over filesets • Grids and cluster	N/A	Resubmission and reliability measurement of task and workflows are supported.
Keplar UC Davis, UC Santa Barbara, and UC San Diego. `https://kepler-project.org/`	• Independently Extensible, Reliable, open and a comprehensive system • Supports multi-disciplinary applications • Grids, clusters, and clouds	Data and process provenance information is recorded.	Resubmissions, checkpointing, alternative versions, error-state and user-defined exception handling mechanisms to address issues are employed.
Cloudbus WF Engine The University of Melbourne, Australia. `http://cloudbus.org/workflow/`	• Easy to use Graphical editor • User-friendly portal for discovery, monitoring and scheduling • Grids, clusters, and clouds	Provenance information of data is recorded.	Failure are handled by resubmitting the tasks to resources.
Taverna Created by the myGrid team.	• Capable of performing iterations and looping • Supports data streaming • Grids, clusters, and clouds	Provenance suite records service invocations and workflow results both intermediate and final.	Resubmission and alternate resources.
e-Science Central Newcastle University, United Kingdom. `http://www.esciencecentral.co.uk/`	• Easy and efficient access through web browser • Provides APIs for external applications • All data are versioned • Private and public clouds	e-SC provenance service collects information regarding all system events.	Provides fine grained security control modeled around groups and user-to-user connections.
SwinDeW-C Swinburne University of Technology, Australia.	• Cloud based peer-to-peer WFMS • Web portal allows users to access entire WFMS • Clouds	data provenance is recorded during workflow execution	Checkpointing is employed. QoS management components includes performance management, data management and security management.

iteration workflow structures. Askalon uses a graphical interface called Teuta to support the graphical specification of grid workflow applications based on the UML activity diagram [53,54].

Askalon can detect faults at the following levels. 1) Hardware level: Machine crashes and network failures. 2) OS level: Exceeded disk quota, out of disk space, and file not found errors. 3) Middleware-level: Failed authentication, failed job-submission, unreachable services and file staging failures. 4) Workflow level: Unavailable input data, data movement faults. However, the system cannot detect task level faults such as memory leak, uncaught exception, deadlock/livelock, incorrect output data, missing shared libraries, and job crashes. Further, the system can recover from the following faults at different levels: 1) Hardware level: Machine crashes and network failures; 2) OS level: Exceeded disk quota, out of disk space; 3) Middleware-level: Failed job-submission; 4) Workflow level: Data movement faults. Nonetheless, it does not recover from task level faults and user-defined exceptions. Fault-tolerant techniques like checkpointing, migration, restart, retry and replication are employed to recover from these faults [53,54,110].

2.8.2 Pegasus

It is a project of the USC Information Sciences Institute and the Computer Science department at the University of Wisconsin Madison, United States. Pegasus enables scientists to construct workflows in abstract terms by automatically mapping the high-level workflow descriptions onto distributed infrastructures (e.g., Condor, Globus, or Amazon EC2). Multiple workflow applications can be executed in this WFMS [3].

Workflows can be described using DAX, a DAG XML description. The abstract workflow describes application components and their dependencies in the form of a DAG [42].

Workflow application can be executed in variety of target platforms including local machine, clusters, grids and clouds. The WFMS executes jobs, manages data, monitors execution and handles failures. Pegasus WFMS has five major components: 1) *Mapper*, generates an executable workflow from an abstract workflow. It also restructures the workflow to maximize performance. It further adds transformations aiding in data management and provenance generation; 2) *Local Execution Engine*, submits jobs to the local

scheduling queue by managing dependencies and changing the state; 3) *Job Scheduler*, schedules and manages individual jobs on local and remote resources; 4) *Remote Execution Engine*, manages execution of one or more tasks on one or more remote nodes; 5) *Monitoring Component*, monitors the workflow execution. It records the tasks logs, performance and provenance information in a workflow database. It notifies events such as failures, success and statuses [43].

Pegasus stores and queries information about the environment, such as storage systems, compute nodes, data location, through various catalogs. Pegasus discovers logical files using the Replica Catalog. It looks up various user executables and binaries in Transformation Catalog. Site Catalog is used to locate computational and storage resources [42, 43].

Pegasus has its own lightweight job monitoring service called Kickstart. The mapper embeds all jobs with Kickstart [43]. This helps in getting runtime provenance and performance information of the job. This information is further used for monitoring the application.

Resource selection is done using the knowledge of available resources, their characteristics and the location of the input data. Pegasus supports pluggable components where a customized approach for site selection can be performed. It has few choices of selection algorithms, such as random, round-robin and min-min.

Pegasus can handle failures dynamically at various levels building on the features of DAGMan and HTCondor. It is equipped to detect and recover from faults. It can detect faults at the following levels: At the Hardware and Operating System levels, it can detect exceeding CPU time limit and file non-existence. At the level of Middleware, it detects authentication, file staging, and job submission faults. At Task and Workflow levels job crashes and input unavailability are detected. DAGMan helps recover the following failures at different levels: at Hardware level, it can recover from machine crashes and network failures by automatically resubmitting. Middleware faults detected can also be recovered. Data movement faults can also be treated with recovery at task and workflow level. At Workflow level, redundancy is used and light-weight checkpoints are supported [43,110]. If a job fails more than the set number of retries, then the job is marked as

a fatal failure. When a workflow fails due to such failures, the DAGMan writes a rescue workflow. The rescue workflow is similar to the original DAG without the fatal failure nodes. This workflow will start from the point of failure. Users can also re-plan the workflow, in case of workflow failures and move the computation left to an alternate resource. Pegasus uses retries, resubmissions, and checkpointing to achieve fault-tolerance [43].

Monitoring and debugging is also done to equip users to track and monitor their workflows. Three different logs are generated which are used to collect and process data [43]. 1) Pegasus Mapper Log helps relate the information about the abstract workflow from the executable workflow allowing users to correlate user-provided tasks to the jobs created by Pegasus. 2) Local workflow execution engine logs contain status of each job of the workflow. 3) Job logs capture provenance information about each job. It contains fine-grained execution statistics for each task. It also includes a web dashboard to facilitate monitoring [43].

2.8.3 Triana

Triana [133] is a data-flow system developed at Cardiff University, United Kingdom. It is a combination of an intuitive graphical interface with data analysis tools. It aims to support applications on multiple environments, such as peer-to-peer and grid computing. Triana allows users to integrate their own middleware and services besides providing a vast library of pre-written tools. These tools can be used in a drag-and-drop fashion to orchestrate a workflow.

Triana addresses fault-tolerance in a user-driven and interactive manner. When faults occur, the workflow is halted, displaying a warning, and allowing the user to rectify. At the hardware level, machine crashes and network errors are detected. Missing files and most other faults can be detected by the workflow engine at the operating system level. With the exception of deadlock and memory leaks that cannot be detected at the middleware and the task level, all other faults can be detected. In the workflow level, data movement and input availability errors are detected. Light-weight checkpointing and restart of services are supported at the workflow level. Retries, alternate task creations, and restarts are supported at the task level by the workflow engine [110].

2.8.4 UNICORE 6

Unicore [129] is a European grid technology developed by collaboration between German research institutions and industries. Its main objective is to access distributed resources in a seamless, secure, and intuitive way. The architecture of UNICORE is divided into three layers namely, *client layer*, *service layer*, and *systems layer*. In the client layer, various clients, like UNICORE Rich Client (graphical interface), UNICORE command-line (UCC) interface, and High Level API (HiLA) a programming API are available.

The service layer contains all the vital services and components. This layers has services to maintain a single site or multiple sites. Finally, the system layer has the Target System Interface (TSI) between the UNICORE and the low-level resources. Recently added functionalities to UNICORE 6 contains support for virtual organizations, interactive access based on X.509 certificates using Shibboleth, and improved data management through the integration of DataFinder. GridBeans and JavaGAT help users to support their applications further. UNICORE 6 also introduces for-each-loops and iteration over file-sets in addition to existing workflow constructs. It also supports resubmission and reliability measurement for task and workflows. Added to these new monitoring tools, availability and service functionality are also improved.

2.8.5 Kepler

The Kepler system [8, 92, 101] is developed and maintained by the cross-project collaboration consisting of several key institutions: UC Davis, UC Santa Barbara, and UC San Diego. Kepler system allows scientists to exchange, archive, version, and execute their workflows.

Kepler is built on Ptolemy, a dataflow-oriented system. It focuses on an actor-oriented modeling with multiple component interaction semantics. Kepler can perform both static and dynamic checking on workflow and data. Scientists can prototype workflows before the actual implementation. Kepler system provides web service extensions to instantiate any workflow operation. Their grid service enables scientists to use grid resources over the internet for a distributed workflow. It further supports foreign language interfaces via

the Java Native Interface (JNI), giving users the benefits to use existing code and tools. Through Kepler users can link semantically compatible but syntactically incompatible services together (using XSLT, Xquery, etc.). Kepler supports heterogeneous data and file formats through Ecological Metadata Language (EML) ingestion. Fault-tolerance is employed through retries, checkpointing, and alternative versions.

2.8.6 Cloudbus Workflow Management System

The WFMS [19, 107, 108] developed at The University of Melbourne provides an efficient management technique for distributed resources. It aids users by enabling their applications to be represented as a workflow and then execute them on the cloud platform from a higher level of abstraction. The WFMS is equipped with an easy-to-use graphical workflow editor for application composition and modification, an XML-based workflow language for structured representation. It further includes a user-friendly portal with discovery, monitoring, and scheduling components.

Workflow monitor of the WFMS enables users to view the status of each task, they can also view the resource and the site where the task is executed. It also provides the failure history of each task. The workflow engine contains workflow language parser, resource discovery, dispatcher, data management, and scheduler. Tuple space model, event-driven approach, and subscription approach make WFMS flexible and loosely coupled in design, as they allow task managers to be independent allowing their communication through events [150]. Failures are handled by resubmitting the tasks to resources without a failure history for such tasks. WFMS uses either Aneka [137] and/or Broker [138] to manage applications running on distributed resources.

2.8.7 Taverna

Taverna [103, 144] is an open source and domain-independent WFMS created by the myGrid team. It is a suite of tools used to design and execute scientific workflows and aid in silico experimentation. Taverna engine is capable of performing iterations, looping, and data streaming. It can interact with various types of services including web services,

data warehouses, grid services, cloud services, and various scripts like R, distributed command-line, or local scripts.

The Taverna server allows workflows to be executed in distributed infrastructures like clusters, grids and clouds. The server has an interface called *Taverna Player* through which users can execute workflows from web browsers or through third-party clients. *Taverna Provenance suite* records service invocations and workflow results both intermediate and final. It also supports pluggable architecture that facilitates extensions and contributions to the core functionalities. Here, retries and alternate resources are used to mitigate failures.

2.8.8 The e-Science Central (e-SC)

The e-Science Central [66] was created in 2008 as a cloud data processing system for e-Science projects. It can be deployed on both private and public clouds. Scientists can upload data, edit, run workflows, and share results using a Web Browser. It also provides an application programming interface through which external application can use the platforms functionality.

The e-SC facilitates data storage management, tools for data analysis, automation tools, and also controlled data sharing. All data are versioned and support reproduction of experiments, aiding investigation into data changes, and their analysis.

The e-SC provenance service collects information regarding all system events and this provenance data model is based on the *Open Provenance Model* (OPM) standard. It also provides fine grained security control modeled around groups and user-to-user connections.

2.8.9 SwinDeW-C

Swinburne Decentralized Workflow for cloud (SwinDew-C) [91] is a cloud based peer-to-peer WFMS developed at Swinburne University of Technology, Australia. It is developed based on their earlier project for grid called SwinDeW-G. It is built on SwinCloud infrastructure that offers unified computing and storage resources. The architecture of

SwinDeW-C can be mapped into four basic layers: *application layer*, *platform layer*, *unified resource layer*, and *fabric layer*.

In SwinDeW-C users should provide workflow specification consisting of task definitions, process structures, and QoS constraints. SwinDeW-C supports two types of peers: An ordinary SwinDeW-C peer is a cloud service node with software service deployed on a virtual machine; and SwinDeW-C coordinator peers, are special nodes with QoS, data, and security management components. The cloud workflow specification is submitted to any coordinated peer, which will evaluate the QoS requirement and determine its acceptance through a negotiation process. A coordinated peer is setup within every service provider. It also has pricing and auditing components. All peers that reside in a service provider communicate with its coordinated peer for resource provisioning. Here, each task is executed by a SwinDeW-C peer during the run-time stage.

SwinDeW-C also allows virtual machines to be created with public clouds providers, such as Amazon, Google, and Microsoft. Checkpointing is employed for providing reliability. Additionally, QoS management components including performance management, data management, and security management are integrated into the coordinated peers.

2.8.10 Big Data Frameworks: MapReduce, Hadoop, and Spark

Recently, big data analytics has gained considerable attention both in academia and industry. Big data analytics is heavily reliant on tools developed for such analytics. In fact, these tools implement a specific form of workflows, known as MapReduce [39].

MapReduce framework is a runtime system for processing big data workflows. The framework usually runs on a dedicated platform (e.g., a cluster). There are currently two major implementations of the MapReduce framework. The original implementation with a proprietary license was developed by Google [39]. After that, Hadoop framework [84] was developed as an open-source product by Yahoo! and widely applied for big data processing.

The MapReduce framework is based on two main input functions, *Map* and *Reduce* that are implemented by the programmer. Each of these functions is executed in parallel on large-scale data across the available computational resources. Map and Reduce collec-

tively form a usually huge workflow to process large datasets. The MapReduce storage functionality for storing input, intermediate, and output data is supported by distributed file systems developed specifically for this framework, such as Hadoop Distributed File System (HDFS) [125] and Google File System (GFS) [60].

More specifically, every MapReduce program is composed of three subsequent phases namely, *Map*, *Shuffle*, and *Reduce*. In the Map phase, the Map function implemented by the user is executed on the input data across the computational resources. The input data is partitioned into chunks and stored in a distributed file system (e.g., HDFS). Each Map task loads some chunks of data from the distributed file system and produces intermediate data that are stored locally on the worker machines. Then, the intermediate data are fed into the Reduce phase. That is, the intermediate data are partitioned to some chunks and processed by the Reduce function, in parallel.

Distributing the intermediate data across computational resources for parallel Reduce processing is called Shuffling. The distribution of intermediate data is accomplished in an all-to-all manner that imposes a communication overhead and often is the bottleneck. Once the intermediate data are distributed, the user-defined Reduce function is executed and the output of the MapReduce is produced. It is also possible to have a chain of MapReduce workflows (a.k.a multi-stage MapReduce), such as Yahoo! WebMap [7]. In these workflows, the output of a MapReduce workflow is the intermediate data for the next MapReduce workflow.

Spark [154] is a framework developed at UC Berkeley and is being utilized for research and production applications. Spark offers a general-purpose programming interface in the Scala programming language [102] for interactive and in-memory data mining across clusters with large datasets. Spark has proven to be faster than Hadoop for iterative applications.

MapReduce has been designed to tolerate faults that commonly occur at large scale infrastructures where there are thousands of computers and hundreds of other devices such as network switches, routers, and power units. Google and Hadoop MapReduce can tolerate crashes of Map and Reduce tasks. If one of these tasks stops, it is detected and a new instance of the same task is launched. In addition, data are stored along with

their checksum on disks that enables corruption detection. MapReduce [39] uses a log-based approach for fault tolerance. That is, output of the Map and Reduce phases are logged to the disk [95] (e.g., a local disk or a distributed file system). In this case, if a Map task fails then it is re-executed with the same partition of data. In case of failure in the Reduce phase, the key/value pairs for that failed Reducer have to be re-generated.

2.8.11 Other Workflow Management Systems

WFMSs are in abundance that can schedule workflows on distributed environments. In this section, we present a brief overview of some of the less predominant systems. These WFMS primarily schedule application on clusters and grids. Karajan [139] is one such WFMS, that was implemented to overcome the shortcoming of GridAnt [9]. It was developed at the Argonne National Laboratory. Karajan is based on the definition of hierarchical workflow components.

Imperial College e-Science Network Infrastructure (ICENI) [97] was developed at London e-science centre, which provides a component-based grid-middleware. GridFlow [24], Grid Workflow Execution Engine [50], P-Grade [77], Chemomentum [22] are other WFMS that schedule workflow applications on grid platforms. Each of these workflow engine have their own unique properties and have different architectures supported by a wide variety of tools and software.

2.9 Tools and Support Systems

2.9.1 Workflow Description Languages

Workflows are complicated constructs that needs to be defined at various levels. There are numerous descriptive languages that can be used to detail every resource and service to the workflow enactment engine.

Language based modeling uses XML based markup language to define abstract workflows [148]. Askalon [53] uses an XML-based language called Abstract Grid Workflow Language (AGWL), which expresses sequence, parallelism, choice and iteration con-

structs in a workflow structure. Kepler [92] describes its input and outputs of web services through web services description language (WSDL), which provides an XML notation. Grid Workflow Engine (GWFE) [108] uses an XML-based workflow language called xWFL for application composition. Similarly, Pegasus [40] denotes its abstract workflow in a XML in the form of a DAX i.e., DAG XML description. Web services do not support detailed description of data, processes and resource at a semantic level, which led to the development of a Simple Conceptual Unified Flow Language (Scufl) [103]. It is an XML-based conceptual language where each processing step represents one atomic task.

Graph based modeling defines workflows through a graphical definition. Users can use drag-and-drop functionality to compose workflows. UML-based models and Petri Nets are the major approaches used in graph based modeling. Teuta [52] is one such graphical specification model based on UML models used as a graphical interface in Askalon. FlowManger and XRL/Flower are few others tools used in other WFMSs [148].

ICENI use a general job description language, JDML [98], which is an XML based language. The BPEL4WS [133] language is used to choreograph the interactions between Web services. It is less common in scientific workflow systems but widely used in business workflows.

Chimera proposed a Virtual Data Language (VDL) [56]. This data system combines a virtual data catalog, with a virtual data language interpreter that translates user requests into data definition and query operations on the database. FreeFluo [103] is another such tool that is integrated into Taverna to transfer intermediate data and invoke services.

2.9.2 Data Management Tools

Workflow enactment engine need to move data from compute nodes to storage resources and also from one node to another. Kepler uses GridFTP [8] to move files, to fetch files from remote locations. Unicore uses a data management system called DataFinder [121]. It provides with management of data objects and hides the specifics of storage systems by abstracting the data management concepts. For archival of data Tivoli Storage Manager [1] could be used. It reduces backup and recovery infrastructure. It can also back up into the

[1] http://www-03.ibm.com/software/products/en/tivostormana/

cloud with openstack and vCloud integrations. Traditional protocols like HTTP, HTTPS, SFTP are also used for data movement.

2.9.3 Security and Fault-Tolerance Management Tools

In SwinDeW-C, secure communications are ensured through GnuPG [2], which is a free implementation of OpenPGP. Globus uses the X.509 certificates, an established secure format for authentication and identification. These certificates can be shared among public key based software [91]. Unicore 6 employs an interactive access based on X.509 certificates called Shibboleth [3] that enables Single Sign-On as well as authentication and authorization. The Interoperable Global Trust Federation[4] (IGTF) is a trust service provider that establishes common policies and guidelines. Similarly, The European Grid Trust project[5] provides new security services for applications using GRID middleware layer.

Access control to services can be attained through access control lists (ACLs), which can be attached to data items so that privileges for specific users and groups can be managed. DAGMan offers fault-tolerance to Pegasus through its rescue DAG. Additionally, provenance plays an important role in fault-tolerance. Most WFMS use Open Provenance Model format[6] and the W3C PROV model[7] to achieve and manage provenance information.

2.9.4 Cloud Development Tools

Infrastructure resources are offered by public and private clouds. Public clouds are offered by many providers like Amazon AWS, Google Compute Engine, Microsoft Azure, IBM cloud and many others. Private clouds could be built using Openstack, Eucalyptus and VMware to name a few. Cloud providers offer many storage solutions that can be used by WFMSs. Some of the storage solutions offered are Amazon S3, Google's BigTable,

[2]https://www.gnupg.org/
[3]http://www.internet2.edu/products-services/trust-identity-middleware/shibboleth/
[4]http://www.igtf.net/
[5]http://www.gridtrust.eu/gridtrust/
[6]http://openprovenance.org/
[7]http://www.w3.org/2011/prov

and the Microsoft Azure Storage. Oracle also offers a cloud based database as a service for business.

Amazon through its Amazon Simple Workflow (SWF) [8] provides a fully-managed task coordinator through which developers can build, run, and scale jobs. Chaos Monkey [9] is a free service that randomly terminates resources in your cloud infrastructures. This helps test the system for failures and help develop fault-tolerant systems in cloud.

2.9.5 Support Systems

*my*Experiment [62] is a social network environment for e-Scientists developed by a joint team from the universities of Southampton, Manchester and Oxford. It provides a platform to discuss issues in development, to share workflows and reuse other workflows. It is a workflow warehouse and a gateway to established environments.

Workflow Generator [2], created by Pegasus provides synthetic workflow examples with their detailed characteristics. They also provide a synthetic workflow generator and traces and execution logs from real workflows.

Failure Trace Archive [81] is a public repository of availability traces of parallel and distributed systems. It also provides tools for their analysis. This will be useful in developing fault-tolerant workflow schedulers.

2.10 Summary

Workflows have emerged as a paradigm for managing complex large scale data analytics and computation. They are largely used in distributed environments such as, grids and clouds to execute their computational tasks. Fault-tolerance is crucial for such large scale complex applications running on failure-prone distributed environments. Given the large body of research in this area, in this chapter, we provided a comprehensive view on fault-tolerance for workflows in various distributed environments.

In particular, this chapter provides a detailed understanding of faults from a generic

[8] http://aws.amazon.com/swf/
[9] https://github.com/Netflix/SimianArmy/wiki/Chaos-Monkey/

viewpoint (e.g. transient, intermittent, and permanent) and a processor viewpoint (such as, crash, fail-stop and byzantine). It also describes techniques such as replication, resubmission, checkpointing, provenance, rescue-workflow, exception handling, alternate task, failure masking, slack time, and trust-based approaches used to resolve these faults by which, a transparent and seamless experience to workflow users can be offered.

Apart from the fault-tolerant techniques, this chapter provides an insight into numerous failure models and metrics. Metrics range from makespan oriented, probabilistic based, reliability based, and trust-based among others. These metrics inform us about the quality of the schedule and quantify fault-tolerance of a schedule.

Prominent WFMSs are detailed and positioned with respect to their features, characteristics, and uniqueness. Lastly, tools such as, those for describing workflow languages, data-management, security and fault-tolerance, tools that aid in cloud development, and support systems (including social networking environments, and workflow generators) are introduced.

Chapter 3

Robust Scheduling with Deadline and Budget Constraints

Dynamic resource provisioning and the notion of seemingly unlimited resources are attracting scientific workflows rapidly into Cloud computing. Existing works on workflow scheduling in the context of Clouds are either on deadline or cost optimization, ignoring the necessity for robustness. Robust scheduling that handles performance variations of Cloud resources and failures in the environment is essential in the context of Clouds. In this chapter, we present a robust scheduling algorithm with resource allocation policies that schedule workflow tasks on heterogeneous Cloud resources while trying to minimize the total elapsed time (makespan) and the cost. Our results show that the proposed resource allocation policies provide robust and fault-tolerant schedule while minimizing makespan. The results also show that with the increase in budget, our policies increase the robustness of the schedule.

3.1 Introduction

CLOUD computing offers virtualized servers, which are dynamically managed, monitored, maintained, and governed by market principles. As a subscription based computing service, it provides a convenient platform for *scientific workflows* due to features like application scalability, heterogeneous resources, dynamic resource provisioning, and pay-as-you-go cost model. However, clouds are faced with challenges like performance variations (because of resource sharing, consolidation and migration) and failures (caused by outages and faults in computational and network components).

The performance variation of Virtual Machines (VM) in clouds affects the overall ex-

ecution time (i.e. makespan) of the workflow. It also increases the difficulty to estimate the task execution time accurately. Dejun et al. [44] show that the behavior of multiple "identical" resources vary in performance while serving exactly the same workload. A performance variation of 4% to 16% is observed when cloud resources share network and disk I/O [10].

Failures also affect the overall workflow execution and increase the makespan. Failures in a workflow application are mainly of the following types: task failures, VM failures, and workflow level failures [67]. Task failures may occur due to dynamic execution environment configurations, missing input data, or system errors. VM failures are caused by hardware failures and load in the data center, among other reasons. Workflow level failures can occur due to server failures, cloud outages, etc. Prominent fault-tolerant techniques that handle such failures are retry, alternate resource, checkpointing, and replication [148].

Workflow management systems should handle performance variations and failures while scheduling workflows. Workflow scheduling maps tasks to suitable resources, whilst maintaining the task dependencies. It also satisfies the performance criteria while being bounded by user defined constraints. This is a well known NP-complete problem [73].

A schedule is said to be robust if it is able to absorb some degree of uncertainty in the task execution time [23]. Robust schedules are much needed in mission-critical and time-critical applications. Here, meeting the deadline is paramount and it also improves the application dependability [59]. Robust and fault-tolerant workflow scheduling algorithms identify these aspects and provide a schedule that is insensitive to these uncertainties, by tolerating variations and failures in the environment up to a certain degree. Robustness of a schedule is always measured with respect to another parameter such as makespan, schedule length, etc. [23]. It is usually achieved with redundancy in time or space [59] i.e. adding slack time or replication of nodes.

In this chapter, we present a robust and fault-tolerant scheduling algorithm. The proposed algorithm is robust against uncertainties such as performance variations and failures in cloud environments. This scheduling algorithm efficiently maps tasks on het-

erogeneous cloud resources and judiciously adds slack time based on the deadline and budget constraints to make the schedule robust. Additionally, three multi-objective resource selection policies are presented, which maximize robustness while minimizing makespan and cost.

The **key contribution** of this chapter is a robust and fault-tolerant scheduling algorithm with three multi-objective resource selection policies. This chapter also presents two robustness metrics and a detailed performance analysis of the scheduling algorithm using them.

3.2 Related Work

Current workflow scheduling on clouds mostly focuses on homogeneous resources [107]. One of the early attempts of exploiting the heterogeneous types of resources is presented by Abrishami et al. [5]. They do not consider budget constraints and their scheduling algorithm does not consider failures or performance variations.

Robust and fault-tolerant scheduling in workflows has been an active area of research with significant amount of work done in the area of grids, clusters, and other distributed systems. Research in robust and fault-tolerant scheduling encompasses numerous fields like job-shop scheduling [85], supply chain [65], and distributed systems [67, 124, 128]. Many scheduling techniques have been employed to develop robust workflows. Dynamic scheduling or reactive scheduling reschedules tasks when unexpected events occur [65]. Trust based scheduling predicts the stability of a schedule by incorporating a trust model for resource providers [142]. Stochastic based approaches model uncertainty of system parameters in a non-deterministic way, which aid heuristic decision making [123, 128]. Robust schedule has also been developed using fuzzy techniques, where task execution times are represented by fuzzy logic, which is also used to model uncertainty [55].

Shi et al. [124] proposed a robust scheduling algorithm using the technique of task slack time. Task slack time represents a time window within which the task can be delayed without extending the makespan and it is intuitively related to the robustness of

the schedule. They present an ϵ-constraint method with deadline as a constraint. This scheduling algorithm does not consider a cloud environment and also does not consider any cost models. However, they find schedules with maximum slack time without exceeding the specified deadline.

To the best of our knowledge, there has been no study in workflow scheduling algorithm for clouds maximizing robustness, and minimizing makespan and cost at the same time. Also there are very few works which schedule workflow tasks on heterogeneous cloud resources. This study tries to address these shortcomings.

3.3 System Model

The description of the system model, important definitions, assumptions, and the problem statement are discussed further in this section.

The **cloud environment** in our system model has a single data center that provides heterogeneous VM/resource types, $VT = \{vt_1, vt_2, ..., vt_m\}$. Each VM type has a specific configuration and a price associated with it. The configuration of VM type differs with respect to memory, CPU measured in million instructions per second (MIPS) and OS. Each vt_i has a $Price(vt_i)$ associated with it, charged on an unit time basis (e.g. 1 hour, 10 minutes, etc.). A static VM startup/boot time is assigned to all VMs, which influences the start time of the task.

Uncertainties: We have considered two kinds of uncertainties, task failures and performance variations of VMs. Performance variations in the system arise due to factors like the data center load, network delays, VM consolidation, etc. Due to the performance variation of a VM, the execution time of a task increases or decreases by a value y. Here, y is a random variable with a certain probability distribution with a mean value of zero. The actual execution time (AET) of a task is calculated as $AET(t_j) = e_j(1 + y)$, where e_j is the expected execution time of task t_j.

A **Workflow** can be represented as a Directed Acyclic Graph (DAG), $G = (T, E)$, where T is a set of nodes, $T = \{t_1, t_2, ..., t_n\}$, and each node represents a task. Here, E represents a set of edges between tasks, which can be control and/or data dependencies.

Each workflow is bounded by a user defined deadline D and budget B constraints. Additionally, each workflow task t_j has a task length len_j given in Million Instructions. We assume all tasks to be CPU intensive and model task execution time accordingly. Models for data or I/O intensive tasks can also be incorporated to estimate task execution without affecting the scheduling algorithm. Task length and the MIPS value of the VM are used to estimate the execution time on a particular VM type. We also account for data transfer times between tasks. The data transfer time between two tasks is calculated based on the size of the data transferred and the cloud data center internal network bandwidth.

Makespan, M, is the total elapsed time required to execute the entire workflow. The deadline D is considered as a constraint where the Makespan M should not be more than the deadline ($M \leqslant D$). The makespan of the workflow is computed as following:

$$M = finish_{t_n} - ST, \tag{3.1}$$

where ST is the submission time of the workflow to the scheduler and $finish_{t_n}$ is the finish time of the exit node.

Total Cost, C, is the total cost of the workflow execution, which is the sum of the price for the VMs used to execute the workflow. Each VM type has a price associated with it, depending on its characteristics and type. The price of each VM is calculated based on its type and the duration of time it was provisioned. The duration of the time is calculated based on the number of hours a VM executes, from the time of its instantiation, until it is terminated or stopped. The time duration is always rounded to the next full hour (e.g. 5.1 hours is rounded to 6 hours). It is important to mention that multiple tasks can execute in a VM depending on the schedule. Moreover, to execute the entire workflow, multiple VMs of different types can be used. Therefore, the total execution cost, C, is the sum price of all the VMs of different types used in the workflow execution. Additionally, there is a budget B as a constraint, such that the total cost should be less than the budget ($C \leqslant B$).

Robustness of a schedule is measured using two metrics. The first metric is *robustness probability*, R_p, which is the likelihood of the workflow to finish before the given

deadline [124], which can be formulated as below:

$$R_p = (TotalRun - FailedRun)/(TotalRun), \tag{3.2}$$

where $TotalRun$ is number of times the experiment was conducted and $FailedRun$ is number of times the constraint, $finish_{t_n} \leqslant D$ was violated. This equation is based on the methodology offered by Dastjerdi et al. [34].

The second metric is the *tolerance time*, R_t, which is the amount of time a workflow can be delayed without violating the deadline constraint. This provides an intuitive measurement of robustness, expressing the amount of uncertainties it can further withstand.

$$R_t = D - finish_{t_n}. \tag{3.3}$$

Assumptions: Data transfer cost between VMs are considered to be zero, as in many real clouds, data transfer inside a cloud data center is free. Storage cost associated with the workflow tasks is assumed to be free, since storage costs have no effect on our algorithm. The data center is assumed to have sufficient resources, avoiding VM rejections due to resource contention. This is not a prohibitive assumption as the resources required are much smaller than the data center capacity.

Problem Statement: The problem we address in this work is to find a mapping of workflow tasks onto heterogeneous VM types, such that the schedule is robust to the uncertainties in the system, and the makespan and cost is minimized, while executing within the given deadline and budget constraints.

3.4 Proposed Approach

In this section, our algorithm and policies are presented. Before presenting the algorithm, some important definitions are detailed. The *critical path* of a workflow is the execution path between the entry and the exit nodes of the workflow with the longest execution time [4]. Critical path determines the execution time of the workflow. The *critical parent (CP)* of t_j is the parent t_p, whose sum of start time, data transfer time and execution time

Algorithm 1: FindPCP(t)

```
1  //Determine the PCP and allocate a VM for it.
   input : task t
2  while t has unassigned parent do
3      PCP ← null, t_j ← t
4      while there exists an unassigned parent of t_j do
5          add critical parent t_p of t_j to PCP
6          t_j ← t_p
7      call AllocateResource(PCP)
8      for t_j ∈ PCP do
9          marks t_j as assigned
10         call FindPCP(t_j)
```

to t_j is maximum among other parent nodes of t_j.

The *partial critical path (PCP)* of node t_j is a group of dependent tasks in the workflow graph. PCP is determined by identifying the unassigned parents. Unassigned parent is a node that is not scheduled or assigned to any PCP. Further, PCP is created by finding the unassigned critical parent of the node, starting at the exit node, and repeating the same for the critical parent recursively until there are no further unassigned parents. Algorithm 1 is invoked by the scheduler and it details the procedure to find the PCP of a node. Partial critical paths can be scheduled on a single resource, optimizing time and cost [4]. This algorithm decomposes the workflow into smaller groups of tasks, which helps in scheduling. PCPs of a workflow are mutually exclusive, i.e., each task can be in only one PCP.

For every PCP, the best suitable VM type with a robustness type is selected. The robustness type defines the amount of slack that will be added to the PCP execution time. It dictates the amount of fluctuation in the execution time a PCP can tolerate. Four types of robustness that can be associated with a PCP are defined: 1) *No robustness*: this robustness type does not add any slack time to the execution time of a PCP. 2) *Slack* : this robustness type adds a predefined limit of time for the PCP execution time i.e. it can tolerate fluctuations in execution time up to a defined limit. 3) *One Node Failure*: in this robustness type, the largest execution time among the PCP nodes is added to the PCP execution time. This robustness type provides sufficient slack time to handle the

failure of the task with the largest execution time in the PCP. 4) *Two Node Failure*: here, the execution time of the largest two nodes is added to the PCP execution time; this is done only when the PCP consists of at least three nodes. PCP with this robustness type can tolerate up to two task failures. Four robustness types up to two node failures are proposed. However, robustness types with higher number of node failures can also be developed.

Algorithm 2 details the selection of a VM type and its associated robustness type. An exhaustive solution set, $SS = \{s_1, s_2, ..., s_{m*l}\}$ is generated, where m is the number of VM types and l is the number of robustness types. The solution set SS consists of solutions with every possible robustness type for every VM type defined. Each solution, $s_i = \{vt_i, RT_i, PCPc_i, PCPt_i\}$, consists of a robustness type (RT_i), PCP cost ($PCPc_i$) and PCP execution time ($PCPt_i$) for VM type vt_i. As m and l are usual smaller in range, typically ranging between 1 and 100 at the most, the time and space required are reasonable.

The solution set SS is reduced based on deadline and budget constraints into a smaller set of feasible solutions. The deadline constraint D is evaluated by adding the PCP execution time of the chosen instance and robustness type with top level and bottom level.

$$TopLevel + PCPt + BottomLevel \leqslant D, \tag{3.4}$$

where *TopLevel* of PCP is the sum of execution times of nodes on the longest path from the entry node to the first node of PCP. *BottomLevel* of PCP is the sum of execution times of nodes on the longest path from the end node of the PCP to the exit node.

Budget Constraint is evaluated by the following equation:

$$PCPc \leqslant PCPb, \tag{3.5}$$

where PCPc is the total cost of the PCP. PCP Budget, $PCPb$, is the amount that can be spent on the PCP; this is decomposed from the overall budget according to the following equation,

$$PCPb = (PCPt/TT) * B, \tag{3.6}$$

where, TT is the total time of the workflow, which is calculated by adding the execution

Algorithm 2: AllocateResource(PCP)

```
1  //Allocate a suitable robust resource to the PCP
   input  : PCP
   output: Robust Resource for PCP
2  //Create Solution Set SS;
3  for Every Instance type do
4      for Every Robustness type do
5          Create Solution set with PCPt and PCPc
6  FS = null;
7  Calculate PCPb according to equation 3.6;
8  //Create a Feasible Solution Set FS;
9  for Every solution in SS do
10     time = PCPt + TopLevel + BottomLevel;
11     if time <= D and PCPc <= PCPb then
12         Add to FS
13 //finds the best solution according to the chosen policy
   RobustResource = findBestSolution(FS, Policy); Assign every task in PCP to the
   RobustResource.
```

times of the tasks on the reference VM type, vt_{ref}. VM with the least MIPS value is considered as the reference type, vt_{ref}. $PCPt$ is the total execution time of the PCP on vt_{ref}. When $PCPb$ is less than LPr, which is the price required to execute on the cheapest resource, then $PCPb$ is assigned the value LPr.

A feasible solution set FS is created using these two constraints as outlined in Algorithm 2.

The *findBestSolution*, function described in Algorithm 2, chooses the appropriate VM type vt_i for a PCP, based on the resource selection policy from the feasible solution set FS. The three resource selection policies used by this method are described in the following section.

3.4.1 Proposed Policies

In this section, three resource selection policies are explained. These policies select the best solution from the feasible solution set FS for each PCP. Each of them has three objectives, namely *robustness*, *time* and *cost* and the priorities among these objectives change

for each of these policies. The description of the policies is given below:

1 **Robustness-Cost-Time (RCT)**: The objective of this policy is to maximize robustness and minimize cost and makespan. This policy sorts the feasible solution set based on the robustness type, and among the solutions with the same robustness type, they are sorted in the increasing order of cost. Solutions with the same robustness type and cost are sorted with increasing order of time. The best solution from this sorted list is picked and the VM type with the associated robustness type is mapped to the tasks of the PCP. Solutions chosen by this policy have high robustness with a lower cost.

2 **Robustness-Time-Cost (RTC)**: RTC policy is similar to RCT policy described above with different priorities. This policy gives priority to robustness, followed by time and finally cost. This policy selects a solution that is robust with lowest possible makespan. Choices of RTC and RCT policies might have the same robustness type, but will vary with respect to the VM type they select. RTC policy selects a solution with high robustness and lowest possible makespan.

3 **Weighted**: With this policy users can define their own objective function using the three parameters (robustness, time and cost) and assign weights for each of them. Each value is normalized by taking the minimum and maximum values for that parameter. The weights are applied to the normalized values of robustness, time and cost, and based on these weights the best solution is selected. Weighted policy is a generalized policy, which can be used to find solutions according to user preferences.

Our algorithm with the chosen policy finds a suitable VM type associated with a robustness type for every PCP. Further, the algorithm allocates the PCP tasks on a VM of the chosen type. The resource allocator, first attempts to find a VM of the specified type among the running VMs. If such a VM is found, the algorithm checks if its end time is less than the start time of the PCP. If this condition is satisfied, the algorithm allocates PCP tasks on this existing VM; otherwise a new VM is created to allocate the tasks. This

reduces the number of VMs instantiated and also minimizes the makespan as new VMs take time to boot, which delays the schedule.

3.4.2 Fault-Tolerant Strategy

Checkpointing is employed in our algorithm as a fault-tolerant strategy. When a task fails, the algorithm resumes the task from the last checkpoint and checkpointing of tasks is done at regular intervals. The robustness type selected by the resource selection policy provides the necessary slack for the failed task. Additionally, checkpointing strategy helps to recover the task from the last checkpoint.

3.4.3 Time Complexity

Creating a Solution Set SS depends on the number of robustness types and VM types. The time complexity for creating such a set is $O(m.l)$, where m is the number of VM types and l is the number of robustness types. The time complexity for sorting and choosing the best solution based on the policy is $O(m\ logm)$. The parameters m and l can take a maximum value of n, where n is the number of tasks. Therefore, the time complexity of AllocateResource is $O(n^2)$. The time complexity of FindPCP is $O(n)$ as the maximum number of times this method can be recursively invoked is equal to the number of tasks n. Hence, the overall time complexity of our algorithm is $O(n^2)$.

3.5 Performance Evaluation

3.5.1 Simulation Setup

CloudSim [21] was used to simulate the cloud environment. It was extended to support workflow applications, making it easy to define, deploy and schedule workflows. A failure event generator was also integrated into the CloudSim, which generates failures from an input failure trace. Five types of workflow applications and two failure models are used in our simulation as described below.

Application Modeling

Three workflows (CyberShake, LIGO, and Montage) were considered. Their characteristics are explained in detail by Bharathi et al. [74]. These workflows cover all the basic components such as, pipeline, data aggregration, data distribution and data redistribution. Three different sizes of these workflows are chosen, small (around 30 tasks), medium (around 100 tasks) and large (1000 tasks).

Resource Modeling

A cloud model with a single data center offering 10 different types of VMs is considered. The characteristics of VMs are modeled similar to the Amazon EC2 instances (t1.micro, m1.small, m1.medium, m1.large, m1.xlarge, m2.xlarge, m2.2xlarge, m2.4xlarge, c1.medium, c1.xlarge). A charging period of 60 minutes is considered for these VMs, similar to the most prominent cloud providers.

Failure Modeling

Two types of failure models are considered for our experiments. First, failures are simulated from failure traces (FT). Due to lack of publicly available cloud specific failure traces, Condor (CAE) Grid failure dataset [147], available as a part of Failure Trace Archive [81] was chosen. Secondly, a failure model with 10% failure probability (FP) is considered, i.e., for each node there is 10% probability of failure based on uniform distribution. The failed nodes may fail again with the same probability until they complete their execution.

Each VM undergoes a performance variation, which affects the task execution time. We model the variance in the task execution time as a normal distribution $y = N(0, \sigma^2)$, where the standard deviation σ is 10% of the execution time of the task, as suggested by Dejun et al. [44]. They have analyzed and presented the performance variations of Amazon EC2 instances in their study.

Reference Algorithms

Two reference algorithms to compare our resource allocation policies are implemented. The first algorithm is a deadline constrained algorithm proposed by Abrishami et al. [5]. The IaaS cloud Partial Critical Path (ICPCP) algorithm, similar to our algorithm, divides the workflow tasks into PCPs. ICPCP is non-robust algorithm bounded by a deadline constraint.

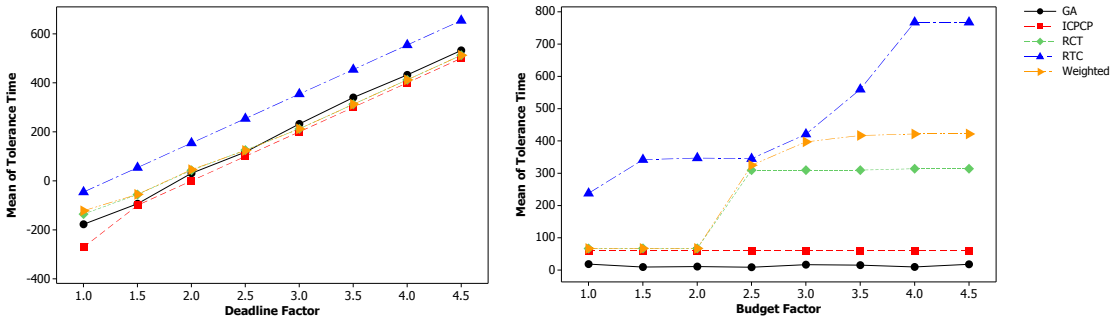
The second reference algorithm implemented is a robust bi-objective genetic algorithm (GA) [124]. This GA considers heterogeneous resources with the objective of maximizing the robustness by increasing the slack time between the tasks. This algorithm considers deadline as a threshold and verifies that the schedule does not violate the deadline. The fitness function, selection and mutation operators for the GA are implemented as described in [124]. The parameters of GA are set as follows: population size = 2000, cross over probability = 0.9 and mutation probability = 0.1, as defined by the authors. Maximum number of iterations is set to 800.

These algorithms are chosen for their similarity with our approach. ICPCP schedules tasks by grouping them into PCPs, similar to our algorithm and GA tries to maximize the slack time to be robust, which is the approach we adapt as well.

In this chapter, we have executed the experiments for three workflow applications with two failure models. For each workflow, we varied the deadline with a fixed budget and also varied the budget keeping the deadline fixed to measure the performance with regards to robustness, makespan and cost. Each experiment was executed 10 times, the mean of which is reported. For the weighted policy, the weights considered for robustness, time and cost are 0.5, 0.3 and 0.2 respectively. We intend to study the effect of varying weights in future. We present our analysis and results in the following section.

3.5.2 Analysis and Results

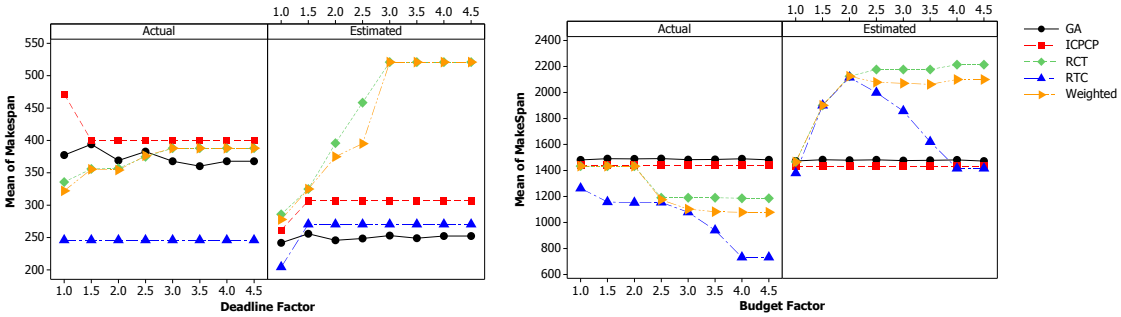
The CyberShake workflow uses the Probabilistic Seismic Hazard Analysis (PSHA) technique to characterize earth-quake hazards in a region and the LIGO Workflow detects gravitational waves of cosmic origin by observing stars and black holes [74]. We present



(a) Cybershake with fixed Budget and with FP failure model

(b) LIGO with fixed Deadline and with FT failure model

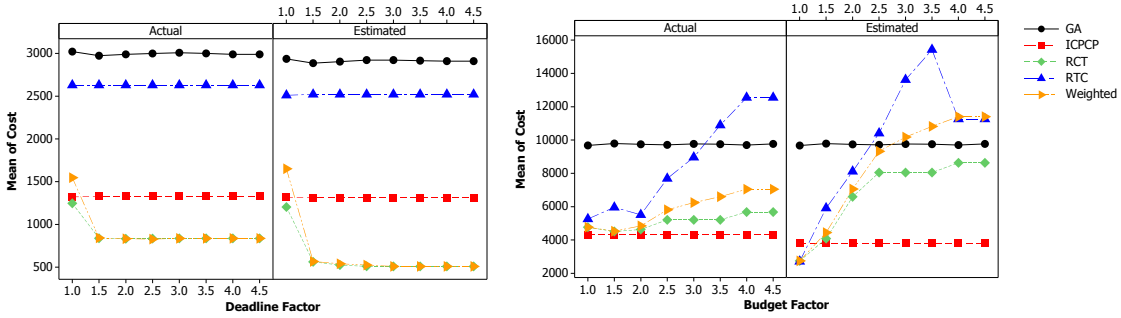
Figure 3.1: Effect on robustness with tolerance time R_t



(a) Cybershake with fixed Budget and with FP failure model

(b) LIGO with fixed Deadline and with FT failure model

Figure 3.2: Effect on makespan for large sized CyberShake and LIGO workflow



(a) Cybershake with fixed Budget and FP failure model

(b) LIGO with fixed Deadline and with a FT failure model

Figure 3.3: Effect on cost for large sized CyberShake and LIGO workflow

Table 3.1: Robustness probability R_p of large montage workflow with failure probability model (FP) for different policies.

Deadline	Budget	ICPCP	GA	RCT	WGHT*	RTC
Strict	Strict	0.00	0.10	0.20	0.40	**0.70**
	Normal	0.00	0.10	0.20	0.70	**0.90**
	Relaxed	0.00	0.00	0.20	0.70	**0.90**
Relaxed	Strict	**1.00**	0.90	**1.00**	**1.00**	**1.00**
	Normal	**1.00**	0.90	**1.00**	**1.00**	**1.00**
	Relaxed	**1.00**	0.80	**1.00**	**1.00**	**1.00**

* WGHT is an abbreviation for the weighted policy.

two experiments considering large workflow types. In the first experiment, we vary the deadline with a fixed surplus budget for large CyberShake workflow and the failures are generated using the failure probability model (FP), with a 10% probability. In the second experiment, we vary the budget with a fixed strict deadline for large LIGO workflow and the failures are generated through the failure trace model (FT). Both these experiments are carefully devised to cover all combinations of deadline and budget, showing the performance of the algorithms under all conditions. For these experiments, we find the lowest makespan M_{low}, which is the time taken to execute on the most expensive VM. We also find the lowest cost C_{low}, which is the cost needed to execute on the cheapest VM. We introduce a deadline factor α similar to [5], based on which we vary the deadlines for workflows according to $\alpha.M_{low}$. We vary α from 1 to 4.5 with a step length of 0.5. Similarly we introduce a budget factor β and the budget is varied according to $\beta.C_{low}$. We vary β from 1 to 4.5 with a step length of 0.5.

The analysis of these experiments and its effect on robustness, makespan and cost are presented below.

Effect on Robustness

Figure 3.1 presents the tolerance time R_t of Cybershake and LIGO workflows. Positive values of R_t represent robust solutions that have finished execution within the deadline even with failures and performance variations. Negative values represent schedules that

have violated the deadline constraint. In Figure 3.1, we observe that the RTC policy has the highest mean tolerance time, conveying that the policy is not just robust but can withstand more failures. RTC policy outperforms other policies emerging as the most robust policy. We observe that robustness increases as deadline or budget increases. We observe in Figure 3.1(b) that tolerance time R_t of ICPCP and GA do not vary with increase in budget. This is because these algorithms do not take budget as an input and do not show any effect as the budget varies.

In 97.5% of the cases weighted policy outperforms ICPCP for CyberShake workflow as seen in Figure 3.1(a). Under strict deadline, weighted and RCT policies perform better than GA in 67.5% of the cases. Under relaxed deadline GA has a higher tolerance time than weighted and RCT policy in 72.5% of the cases, but the cost of execution for GA is 2.6 times higher than RCT and weighted policies. RCT and weighted policies tries to achieve a robust solution while minimizing cost, even under a relaxed deadline we have a robust solution with costs much lower than GA.

In the LIGO workflow experiment, we see that our policies have higher tolerance time in comparison to ICPCP and GA algorithm as shown 3.1(b). We can also observe that the mean tolerance time increases with increase in budget for our policies unlike ICPCP and GA.

Table 3.1 presents the robustness probability R_p for the large Montage workflow with varying deadline and budget. We report the large Montage workflow as it is the most complex and failures in its task nodes have high adverse effect on the makespan and cost. Other workflows show similar trends and have better results for our policies. This table provides a measure of robustness probability, R_p, which is the probability of a schedule being within the deadline. In this table, the deadline factor between 1.0 to 1.5 is considered strict and values between 1.5 to 4.5 are considered relaxed. Similarly, for budget, the budget factor between 1.0 to 1.5 is considered strict, values between 1.5 to 3.0 are considered normal, and values between 3.0 to 4.5 are considered relaxed.

It can be seen that the RTC is the most robust policy and has the highest probability of being within the deadline. The robustness probability, R_p for weighted and RCT policies outperform GA and ICPCP. It can also be observed that our policies perform with high

levels of robustness even under strict deadlines and budgets.

Effect on Makespan

Figure 3.2 shows the effect on makespan for CyberShake and LIGO workflows. Figures 3.2 and 3.3 have graphs with two panels, where the actual panel represents schedules after execution with uncertainties and the estimated panel depicts schedules before execution without failures. Figures 3.2(a) and 3.2(b) show that makespan increases as deadline increases and makespan decreases as budget increases. Our policies have a higher makespan when the schedule is estimated in comparison to ICPCP or GA; however the actual makespan after failures and performance variations of resources is comparatively minimal for our policies. RTC provides schedules with smallest makespan under the scenarios of failures and performance variations because it chooses robust resources with least execution time. The average makespan of weighted policy is 19% lower than ICPCP for both CyberShake and LIGO workflows. The average makespan of RCT policy is 14% and 11% lower than ICPCP for CyberShake and LIGO workflows respectively.

In Figure 3.2(b), the estimated panel of the graph shows the working of the RTC policy. As the budget increases, the makespan increases steadily and then decreases steadily as shown. This is because as the budget increases, the algorithm has the flexibility to either add more slack time or choose an expensive VM. Therefore, with smaller increase in budget, the algorithm chooses inexpensive VMs and adds slack time based on the increases in budget, which increases the estimated makespan. With sufficient increase in budget, the algorithm chooses expensive VM resulting in the decrease of the estimated makespan. The actual panel of the graphs shows that the makespan of our policies are much lower than ICPCP and GA. The RTC policy gives lower makespan consistently, while the makespan of RCT and weighted policies increases slightly with increase in deadline and decreases with increase in budget.

Effect on Cost

Figure 3.3 presents the effects on cost, Figure 3.3(a) shows that the cost decreases for RCT and weighted policies, as the deadline increases with a fixed budget and Figure 3.3(b) shows that cost increases for our policies as budget increases with a fixed deadline.

For CyberShake workflow, we observe that our policies RCT and weighted have lower costs in comparison with ICPCP and GA. RTC policy has a 98% higher cost than ICPCP and 12% lower cost than GA, but has a 39.7% and 33.6% lower makespan than ICPCP and GA respectively. RTC policy chooses resources that are robust with a lower makespan; on the other hand RCT policy chooses a robust schedule with lower costs.

For LIGO workflow, as depicted in Figure 3.3(b) we see increase in costs for our policies as the budget increases, but we can also observe that the robustness increases and makespan decreases with increasing budget as shown in Figure 3.1(b) and 3.2(b). We can see that the costs of our policies are much lower than GA in most of the cases.

Experiments show that our policies consistently offer schedules with high robustness. RTC policy gives robust schedules with increase in costs but lower makespan, and RCT policy provides robust schedules, which minimizes costs under relaxed deadline or increases costs under surplus budget. Under strict deadline or a stringent budget our policies behave comparable to ICPCP with respect to cost, yet provides a robust schedule with lower makespan. Our weighted policy in this experiment is tested with only one set of weights, which are comparable to our RCT policy and hence the results show similar trends. The users can use this policy according to their priorities and get schedules that are aligned to their priorities.

3.6 Summary

This chapter presents three resource allocation policies with robustness, makespan and cost as its objectives. This is one of the early works in robust and fault-tolerant workflow scheduling on clouds, considering deadline and budget constraints. The resource allocation policies judiciously add slack time to make the schedule robust considering the deadline and budget constraints. We test our policies with two failure models for three

scientific workflows with two metrics for robustness. Results indicated that our policies are robust against uncertainties like task failures and performance variations of VMs. As a future work, we propose to validate the proposed algorithm in a realistic cloud environment.

Among the proposed policies presented, the RTC policy shows the highest robustness and at the same time minimizes makespan of the workflow. The RCT policy provides a robust schedule with costs marginally higher than the reference algorithms considered. The weights of the weighted policy can be varied according to the user priorities. Overall, our policies provide robust schedules with the lowest possible makespan. They also show that with increase in budget, our policies increase the robustness of the schedule with reasonable increase in cost.

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Chapter 4

Fault-Tolerant Scheduling Using Spot Instances

Scientific workflows are used to model applications of high throughput computation and complex large scale data analysis. In recent years, Cloud computing is fast evolving as the target platform for such applications among researchers. Furthermore, new pricing models have been pioneered by Cloud providers that allow users to provision resources and to use them in an efficient manner with significant cost reductions. In this chapter, we propose a scheduling algorithm that schedules tasks on Cloud resources using two different pricing models (spot and on-demand instances) to reduce the cost of execution whilst meeting the workflow deadline. The proposed algorithm is fault tolerant against the premature termination of spot instances and also robust against performance variations of Cloud resources. Experimental results demonstrate that our heuristic reduces up to 70% execution cost as against using only on-demand instances.

4.1 Introduction

CLOUD computing is increasingly used amidst researchers for scientific workflows to perform high throughput computing and data analysis [89]. Numerous disciplines use scientific workflows to perform large scale complex analyses. Workflows enable scientists to easily define computational components, data and their dependencies in a declarative way. This makes them easier to execute automatically, improving the application performance, and reducing the time required to obtain scientific results [75,76].

Clouds are realizing the vision of utility computing by delivering computing resources as services. This is facilitating Cloud providers to evolve various business models

around these services. Most providers provision Cloud resources (e.g., Virtual Machines (VMs) instances) on a pay-as-you-go basis charging fixed set price per unit time. However, Amazon, one of the pioneers in this space, started selling idle or unused data center capacity as Spot Instances (SI) from around December 2009. The provider determines the price of a SI (spot price) based on the instance type and demand within the data center, among other parameters [71]. Spot price of a instance varies with time and it is different for different instance types. The price also varies between regions and availability zones. Here, the users participate in an auction-like market and bid a maximum price they are willing to pay for SIs. The user is oblivious to the number of bidders and their bid prices. The user is provided the resource/instance whenever their bid is higher than or equal to the spot price [1]. However, when the spot price becomes higher than the user bid, Amazon terminates the resources. Users do not pay the bid price, they pay the spot price that was applicable at the start time of the instance. Users are not charged for the partial hour when terminated by the provider. Nevertheless, when the user terminates the instance, they have to pay for the full hour.

On-demand and SIs have the same configurations and characteristics. Nonetheless, SIs offers Cloud users reduction in costs of up to 60% for multiple applications like bag-of-tasks, web services and MapReduce workflows [105, 140]. Significant cost reductions are achieved due to lower QoS, which make them less reliable and prone to out-of-bid failures. This introduces a new aspect of reliability into the SLAs and the existing trade-offs making it challenging for Cloud users [71].

Scientific workflows can benefit from SIs with an effective bidding and an efficient fault-tolerant mechanism. If such a mechanism could tolerate out-of-bid failures, it would help reduce the cost immensely.

In this chapter, we present a just-in-time and adaptive scheduling heuristic. It uses spot and on-demand instances to schedule workflow tasks. It minimizes the execution cost of the workflow and at the same time provides a robust schedule that satisfies the deadline constraint. The scheduling algorithm, for every ready task, evaluates the critical path and computes the slack time, which is the time difference between the deadline and

[1] http://aws.amazon.com/ec2/purchasing-options/spot-instances/

the critical path time. The main motivation of the work is to exploit SIs to the extent possible within the slack time. As the slack time decreases due to failures or performance variations in the system, the algorithm adaptively switches to on-demand instances. The algorithm employs a bidding strategy and checkpointing to minimize cost and to comply with the deadline constraint. Checkpointing can tolerate instance failures and reduce execution cost, in spite of an inherent overhead [120] .

The **key contributions** of this chapter are: 1) A just in-time scheduling heuristic that uses spot and on-demand resources to schedule workflow tasks in a robust manner. 2) An intelligent bidding strategy that minimizes cost.

4.2 Related Work

Multiple applications use SIs for resource provisioning. Voorsluys et al. [140] use SIs to provision compute-intensive bag-of-tasks jobs constrained by deadline. They show that applications can run faster and economically by reducing costs up to 60%. However, they use a bag-of-task application and use only SIs to execute the jobs. Mazzucco et al. [96] exploit SIs for providing web services as a Software-as-a-Service(SaaS). They develop an optimal and truthful bidding scheme to optimize revenue. Chohan et al. [29] similarly use SIs for MapReduce workflows to reduce costs and also detail the effects of premature failures. Ostermann et al. [105] study the impact of using SI with grid resources for scientific workflows. They use SIs when grid resources are not available and use static bidding mechanism to show reduction in cost.

In this work, we schedule workflow tasks entirely on Cloud resources, exploiting both spot and on-demand instances to minimize the cost. This work presents a dynamic and adaptive scheduling heuristic, whilst providing a robust schedule. An intelligent and adaptive bidding strategy is also presented, which bids such that the price is minimized.

Amazon does not reveal the details of spot price modeling and their market strategies. Therefore, understanding the dynamics of the market and the frequency of price changes is crucial for bidding effectively. Javadi et al. [71] provide a comprehensive analysis of SIs. They analyze the spot market with respect to two parameters: spot price and inter-

price time i.e. the time between price changes. They also propose a statistical model representing the spot price dynamics as a mixture of Gaussian distributions and inter-price time as an exponential distribution, which models spot price with a high degree of accuracy.

Yehuda et al. [11] provide a model through reverse engineering. They speculate that prices are not always market-driven, but generated randomly via a dynamic hidden reserve price. Reserve price is a hidden price below which Amazon ignores all bids. These works give a deeper understanding of the price dynamics of the spot market and help in modeling the same.

Yi et al. [3] have simulated how checkpointing policies reduce costs of computations by providing fault-tolerance using EC2 SIs. Their evaluation shows that in spite of the inherent overhead, checkpointing schemes can tolerate instance failures. We also use checkpointing policy as a fault-tolerant mechanism and to further reduce computation costs.

The details of our system model and heuristics are discussed in the following sections.

4.3 Background

A **Workflow** is represented as a Directed Acyclic Graph (DAG), as mentioned in Section 3.3. Each workflow is bounded by a user defined deadline D. We also account for data transfer time between tasks. The data transfer time between two tasks is calculated based on the size of the data transferred and the Cloud data center internal network bandwidth. Additionally, each workflow task t_j also has a task length len_j given in Million Instructions, which is used to estimate the task execution time. For each workflow, a dummy exit and entry node is added to have one start and end node.

Makespan, M, is the total elapsed time required to execute the entire workflow. The deadline D is considered as a constraint, where makespan should not be more than the deadline ($M \leqslant D$). The makespan of the workflow is computed as $M = finish_{t_n} - ST$, where ST is the submission time and $finish_{t_n}$ is finish time of the exit node of the workflow.

Pricing models: In our model, we adapt two types of instances from the Amazon model, which vary in their pricing structure. The two pricing models considered are: 1) *On-Demand instance*: the user pays by the hour based on the instance type. 2) *Spot Instance*: users bid for the instance and it is made available as long as their bid is higher than the spot price. Spot prices change dynamically and it can change during the instance runtime. The price of a SI (spot price) is determined by the provider based on the instance type and demand within the data center, among other parameters [71].

Critical Path, CP, is the longest path from the start node to the exit node of the workflow. Critical path determines the makespan of a workflow. The critical path is evaluated in a breadth-first manner calculating the weights of each node. The node weight is the maximum among the predecessors' estimated finish time and the data transfer time calculated as per Equation 4.1 given by Topcuoglu et al. [135],

$$weight(t_i) = \max_{t_p \in pred(t_i)} \{weight(t_p) + w_p + c_{p,i}\} \tag{4.1}$$

where, $pred(t_i)$ is all the parent nodes of t_i, w_i is the execution time of node t_i on an instance type chosen by the algorithm. $c_{p,i}$ is the data transfer time from node t_i to t_p. The maximum weight among the exit nodes is the critical path time. When a node completes execution its weight and data transfer time to all its child nodes is made zero, and the critical path is recomputed.

Latest Time to On-Demand, LTO is the latest time the algorithm has to switch to on-demand instances to satisfy the deadline constraint. The algorithm exploits the spot market before the LTO and switches to on-demand instance later. LTO aids in choosing the right instance, to speed up or slow down and choose the apt pricing model. It is determined for every ready task and the scheduling decisions are made based on the current time t and the LTO. LTO at time t is the difference between the deadline and the critical path ($LTO_t = D - CP_t$).

Total Cost, C, is the sum of the cost of all the instances used for the workflow execution, based on their instance type and pricing model. The cost of each instance is calculated as per the Amazon model. If the instance is an on-demand instance, the on-demand price of that instance is used. If the instance is spot, the spot price of the instance

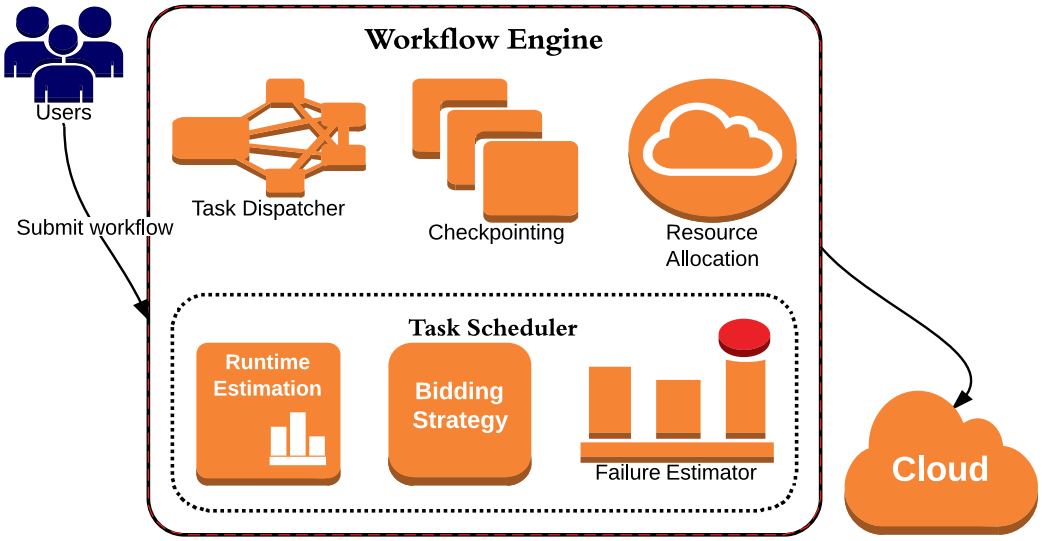

Figure 4.1: System architecture.

is used to calculate the cost. All partial hours are rounded up to full hours for both spot and on-demand instances (e.g. 5.1 hours is rounded up to 6 hours).

4.4 System Model

The system architecture is presented in Figure 4.1. The *workflow engine* acts as a middle layer between the user application and the Cloud. Users submit a workflow application into the engine, which schedules the workflow tasks, provides fault tolerance mechanism, and allocates resources in a transparent manner.

The *Dispatcher* analyses the data and/or control dependencies between the tasks and submits the ready tasks to the task scheduler. Ready tasks are those tasks whose predecessor tasks have completed their execution and have received all input files, and are prepared to be scheduled.

Fault Tolerant Strategy: SIs are prone to out-of-bid failures and an efficient fault tolerant strategy is crucial for a deadline constraint workflow scheduling. Checkpointing is an effective fault tolerant mechanism [120] for spot markets, it takes a snapshot periodically and saves redundant computation in case of failure. It is especially useful in a SI scenario as we save partial computation in the event of failure and do not pay for that. We use

checkpointing mechanism as a fault tolerant strategy. Checkpoints are taken periodically at a user defined frequency. A static checkpointing overhead time is taken into account. However, the cost of storing checkpoints is not considered, as the price of storage service is negligible compared to cost of VMs [120]. Moreover, checkpointing can be done in parallel with the computation, so the time taken to transfer checkpointing data is ignored as it is insignificant.

Resource Allocation: Task scheduler chooses Cloud resource type and also the pricing model (e.g. spot or on-demand). This module allocates the appropriate resource as chosen by the task scheduler.

The *task scheduler* employs a scheduling algorithm to find a suitable Cloud resource for every task. The details of the scheduling algorithm are outlined in the next section.

Runtime Estimation: To determine the runtime of a workflow task on a particular instance type, we use Downey's analytical model [47]. Downey's model requires a task's average parallelism A, coefficient of variance of parallelism σ, the task length and the number of cores of the target instance type to estimate the runtime. We have used the model of Cirne et al. [30] for generating the values of A and σ for each task. This model has been shown to capture the behavior of moldable jobs in parallel production environments. With the use of these two models the task's runtime is estimated on different instance types.

Failure Estimator estimates the failure probability, FP of a particular bid price (bid_t) based on the spot price history. The history price of one month prior to the start of the execution and the spot prices until the point of estimation is used. The failure probability estimator analyzes the spot price history for the bid value in consideration, for which the total time of the spot price history, HT, and the total out of bid time, OBT_{bid_t} for the bid bid_t is measured. The total out of bid time is the aggregated time in history when the spot price was higher than the bid bid_t. These two factors are used to estimate the probability of failure as shown in Equation 4.2. This estimation is used while evaluating the bid value and also while scheduling the task.

$$FP_{bid_t} = OBT_{bid_t} / HT \tag{4.2}$$

The **problem** we address in this work is to find a mapping of workflow tasks onto heterogeneous VM types, using a mixture of on-demand and SIs such that the cost of workflow execution is minimized within the deadline. The schedule should also be robust against premature termination of SIs and performance variations of the resources.

Assumptions: Data transfer cost between VMs are considered to be zero, as in most public Clouds, data transfer inside a Cloud data center is free. The data center is assumed to have sufficient resources, avoiding VM rejections due to resource contention. This is not a prohibitive assumption as the resources required are much smaller than the data center capacity. The number of VM types available and the number of VM types used by the workflow engine are known and limited. Additionally, only one task is executed on an instance at a particular time

4.5 Proposed Approach

4.5.1 Scheduling Algorithm

The proposed just in-time scheduling algorithm maps ready tasks submitted by the task dispatcher onto Cloud resources. It selects a suitable instance type based on the deadline constraint and the *LTO*. The algorithm along with a suitable instance type also selects an apt pricing model to minimize the overall cost. The outline of the algorithm is given in Algorithm 3. Mapping workflow tasks onto heterogeneous instance types with different pricing models is a well known NP-complete problem [73]. Hence, we propose a heuristic to address the same.

The crux of the algorithm is to map tasks that arrive before the *LTO* to SIs and those that arrive after the *LTO* to on-demand instances. In this approach, a single SI type is used. This instance has lowest cost. The rationale behind this is to minimize the overall execution cost. On the other hand, multiple types of on-demand instances are used. This helps to speed up and slow down execution.

Initially, *CP* and *LTO* are computed before the workflow execution. They are recomputed for all ready tasks during execution. Whilst recomputing the *CP* time, if there are any running tasks in the critical path, the time left for their execution is only accounted.

This reflects a realistic *CP* time at that point, giving the algorithm a strong approximation of the time left for the completion of the workflow.

Run time of a particular task varies with different instance types. Similarly, the critical path also varies depending on the instance type used to estimate the same. Henceforth, the *LTO* also varies accordingly. The scheduling decision changes depending on the instance type used to estimate the critical path. We have developed two algorithms keeping this aspect in consideration, namely Conservative and Aggressive.

Conservative algorithm: it estimates the *CP* and *LTO* on the lowest cost instance type. The *CP* estimated in this approach is usually the longest. Hence, it uses SIs only when the deadlines are relaxed. Under tight and moderate deadlines, it does not generate enough slack time to utilize SIs and therefore maps tasks predominantly to on-demand instances. It is conservative in approach and utilizes SIs in a cautious manner only under relaxed deadline making it more robust.

Aggressive algorithm: it estimates the *CP* and *LTO* on a highest cost instance type. Here, the *CP* is smaller than the Conservative algorithm. This approach generates more slack time than the Conservative algorithm and therefore uses SIs even with a strict deadline. This offers significant reduction in cost under moderately relaxed deadline. Under relaxed deadline both algorithms perform similarly. When the market is volatile inducing failures, this approach has less slack time. Hence, it has to opt for on-demand instances that are expensive, increasing the overall cost. The performance of these two algorithms is investigated in the evaluation section.

Algorithm 5 outlines the generic heuristic, which is common to both Conservative and the Aggressive algorithms. When a new task is ready to be mapped, the algorithm through the method *FindFreeSpace* tries to pick free slots among the existing running instances. Free slots are those time slots in an active running instance, when no task is being executed. If there is no free slot it searches for a running instance that will be free before the task's latest start time. Latest start time is the latest time a task can start its execution such that the whole workflow can finish within the deadline. Finding such free slots reduces cost as the algorithm avoids creating new instances for every task. This also saves time as the initiation time for starting a new instance is avoided. Additionally, the

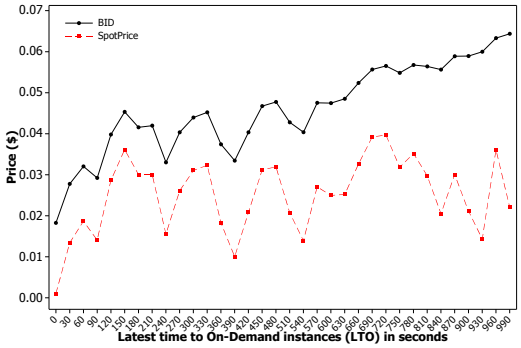

Figure 4.2: Generation of bid value through Intelligent Bidding Strategy.

algorithm creates a new instance when there are no existing instances available before the latest start time of the task.

SIs offer the compute instance at a much lower price. These are terminated prematurely if the bid price goes below the spot price. The failure of SIs is governed by the bid price. Hence, an intelligently calculated bid price reduces the risks of failures. The bid price is provided by one of the bidding strategies, which is explained later. If the bid price is higher than the on-demand price, the algorithm chooses on-demand instances as they offer higher QoS, as shown in line 15-16. Additionally, the bid price fluctuates with the spot price. Therefore, the algorithm makes sure the bid price is higher than the previous bid price, if not the previous bid price is used. The algorithm also estimates the failure probability of a bid price based on the spot price history (line 17-19). Failure probability of the current bid price is estimated by the failure estimator as explained earlier. If the failure probability is higher than a user defined threshold, the algorithm chooses on-demand instance instead of SI. Lines 14-19 of the Algorithm 5 show that, while creating a SI, it also evaluates the risk propositions and bids intelligently. SI with the calculated bid price is instantiated by the resource provisioner.

The other important aspect of the algorithm is choosing the right instance type. When the algorithm chooses SIs, it selects the cheapest instance type to minimize the cost. However, while choosing on-demand instances the algorithm has to select a cost-effective instance type to satisfy the deadline constraint. The *FindSuitableInstances* method in Line 20 computes the critical path time for all instance types and creates a list of instance types whose critical path time satisfy the deadline constraint. The algorithm further tries

to find an already running instance of type contained in the list to assign to the task. If no suitable instance type is found, the $FindCostPerfEffectiveVM$ method estimates the critical path time for the each instance type. It then calculates the cost of the estimated critical path times with their respective on-demand prices. The instance that can execute with the lowest cost is selected. The algorithm does not select an instance type with lowest price, it selects an instance whose price to performance ratio is the lowest. Further, through the resource provisioner the selected instance type is instantiated.

The *time complexity* for calculating the critical path and re-computing the same for all ready tasks is $O(n^2)$ in the worst case, where n is the number of tasks. The complexity of the algorithm for finding a suitable instance for every task is $O(n)$. The complexity of finding the suitable instance depends on the number of instances considered, which is negligible. Hence, the asymptotic time complexity of the algorithm is $O(n^2)$.

4.5.2 Bidding Strategies

Three bidding strategies are presented here, which are used by the scheduling algorithm to obtain a bid price whilst instantiating a SI.

1. **Intelligent Bidding Strategy:** this strategy takes into account the current spot price (p_{spot}), on-demand price (p_{OD}), failure probability (FP) of the previous bid price, LTO, the current time (CT), α and β. α, as seen in Equation 4.3, dictates how much higher the bid value must be above the current spot price. β determines how fast the bid value reaches the on-demand price. FP of the previous bid is used as a feedback to the current bid price, the current bid price varies in accordance to the FP adding intelligence to the bidding strategy. The bid price is calculated according to Equation 4.3 given below. The bid value increases gradually with the workflow execution and as the CT moves closer to the LTO. The bid starts around the initial spot price and ends closer to the on-demand price. The rationale of increasing the bid price is to lower the risk of out-of-bid events as the execution nears the LTO making sure that the deadline constraint is not violated. Lower the value of α, higher is the value of the bid w.r.t the spot price. Figure 4.2 shows the working on this bidding strategy with spot price varying with time, it also shows that the

Algorithm 3: Schedule(t)

```
   input : task t_i
 1 vms ← all VMs currently in the pool;
 2 types ← available instance types;
 3 estimates ← compute estimated runtime of task t_i on each type ∈ types;
 4 Recompute CP and LTO.
 5 timeLeft = LTO − currentTime
 6 if timeLeft > 0 then
 7     decision ← FindFreeSpace(t_i, vms, PriceModel.ANY);
 8     if decision.allocated = true return decision;
 9     if decision.allocated = false then
10         decision ← FindRunningVM(t_i, vms, PriceModel.ANY);
11         if decision.allocated = true return decision;
12 timeLeft = timeLeft − vmInitTime
13 if timeLeft > 0 then
14     bid ← EstimateBidPrice(t_i, type);
15     if bid > on-demand price then
16         Map to on-demand instance and return decision.
17     failProb ← EstimateFailureProbability(bid);
18     if failProb < threshold then
19         Map to spot instance and return decision;
20 InstanceList ← FindSuitableInstances(CP, D)
21 decision ← FindFreeSpace(t_i, InstanceList, PriceModel.ONDEMAND);
22 if decision.allocated = true return decision;
23 if decision.allocated = false then
24     decision ← FindRunningVM(t_i, InstanceList, PriceModel.ONDEMAND);
25     if decision.allocated = true return decision;
26 // If no running instance is found from InstanceList return decision ←
   FindCostPerfEffectiveVM(t_i, InstanceList);
```

bid value steeps up towards the end to reach closer to the on-demand price. This increase in bid price closer to the on-demand price as the CT reaches closer to the LTO is attributed to the parameter β. The higher value of β, the faster the bid reaches closer to on-demand price. The bidding strategy considers all these factors and calculates a bid value in accordance to the situation.

$$\gamma = (-\alpha(LTO - CT))/FP$$

$$bid = e^{\gamma} * p_{OD} + (1 - e^{\gamma} * (\beta * p_{OD} + (1 - \beta) * p_{spot})) \tag{4.3}$$

2. **On-Demand Bidding Strategy** uses the on-demand price as the bid price.

3. **Naive Bidding Strategy:** uses the current spot price as the bid price for the instance.

4.6 Performance Evaluation

4.6.1 Simulation Setup

CloudSim [21] was used to simulate the Cloud environment. It was extended to support workflow applications. It was also extended to model the Amazon spot market. It uses Amazon spot market traces to simulate spot prices.

Application Modeling: Large LIGO workflow with size of 1000 tasks was considered, its characteristics is explained in detail by Juve et al. [74]. This workflow covers all the basic components such as, pipeline, data aggregation, data distribution and data redistribution.

Resource Modeling: A Cloud model with a single data center is considered. The VMs/Cloud resources are modeled similar to Amazon EC2 instances. We have considered 9 instance types (m1.small, m1.medium, m1.large, m1.xlarge, m3.xlarge, m3.2xlarge, m2.xlarge, m2.2xlarge, m2.4xlarge) for on-demand instances and m1.small for SI. The prices of on-demand instances are adapted from the Linux based instances of Amazon EC2 US West region (North California availability zone). The spot price history is taken from the same region from the period of July 2013 - October 2013. The spot price for

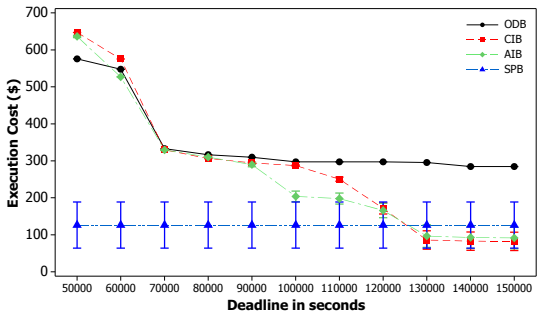

Figure 4.3: Mean execution cost of algorithms with varying deadline (with 95% confidence interval).

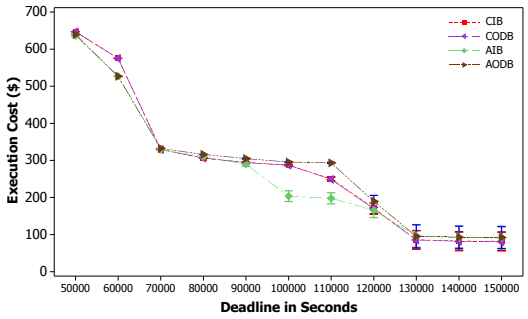

Figure 4.4: Mean execution cost of bidding strategies with varying deadline (with 95% confidence interval).

this period has a mean of $0.05475 with a standard deviation of 0.239 and a minimum of $0.007 and a maximum of $3. In this period, the spot market has around 445 peaks exceeding the on-demand price, making it highly volatile and a suitable time period for testing our methods. A charging period of 60 minutes is considered. A boot/startup time of 100 seconds is considered for each instance [94].

Baseline Algorithms: We developed six baseline algorithms to compare our heuristics and bidding strategy. We developed a full *on-demand baseline algorithm (ODB)* which works similar to our conservative algorithm but maps tasks only to on-demand instances. Similarly, we developed a full *spot baseline algorithm (SPB)*, which uses only SIs with a naive bidding strategy. Additionally, a *conservative with on-demand bidding strategy (CODB)*, *conservative with naive bidding strategy (CNB)*, *aggressive with on-demand bidding strategy (AODB)* and *aggressive with naive bidding strategy (ANB)* are also presented.

4.6.2 Analysis and Results

In this section, we discuss the execution cost incurred by our algorithms, effect of bidding strategies on execution cost, and also the effect of checkpointing on our model. Here, the performance of the algorithms *Conservative with intelligent bidding (CIB)* and *Aggressive with intelligent bidding (AIB)* is investigated against the baseline algorithms. Each experiment runs for 30 times, on each run we randomly change the execution start time in the spot trace, to experience the effect of different price changes. The average value of these 30 runs is reported. Additionally, a sensitivity analysis for the Intelligent Bidding Strat-

egy parameters α and β was performed. Values 0.0005 and 0.9 for α and β respectively gave the best results, which are used in the following experiments. Failure threshold parameter value was set to 1 in these experiments, to demonstrate the working of the algorithm and the bidding strategy.

In our experiments, the deadline varies from strict to moderate to relaxed. A strict deadline being one where high performance instances are needed to complete the execution (e.g. deadlines 50000-80000 seconds in Figures 4.3, 4.4 and 4.5). A moderate deadline is met using a combination of low and high performance instances (e.g. deadlines between 90000-120000). Lastly, a relaxed deadline can be achieved using slow performance instances (e.g. deadlines above 130000).

The monetary cost incurred by our algorithms can be observed in Figure 4.3. AIB and CIB perform similar to on-demand baseline algorithm with strict and relaxed deadline. AIB algorithm starts using SIs under moderately relaxed deadline giving 28.8% reduction in costs in comparison to ODB and 13.7% w.r.t CIB algorithm. When the deadline is lenient, AIB reduces cost as large as 67.5% w.r.t ODB. On the other hand, the CIB uses SIs more cautiously. CIB offers 16.6% lower cost in comparison to the ODB algorithm when the deadline is moderately relaxed. However, when the deadline is relaxed, it generates saving as high as 71% compared to ODB algorithm. CIB and AIB predominantly use on-demand instances when the deadline is strict. Therefore, have higher costs with lower deadline violations. They also perform better under relaxed deadline as compared to SPB. This is because they use an efficient bidding strategy and use SIs only when its price is lower than the on-demand price. Thenceforth, the costs of CIB and AIB under relaxed deadline are 25.8% and 33.7% lower than SPB respectively.

The effectiveness of our bidding strategy is presented in Figure 4.4. Our bidding strategy is compared against the on-demand bidding strategy, which bids the on-demand price of the instance. Figure 4.4 shows that Conservative algorithm performs similarly with both the bidding strategies. However, the aggressive algorithm performs better under intelligent bidding strategy, especially with moderate deadlines. AIB saves 20.3% cost as against AODB. AIB is able to reduce cost as it bids low initially, and since it has enough slack time it is able to tolerate out-of-bid failures. Additionally, checkpointing

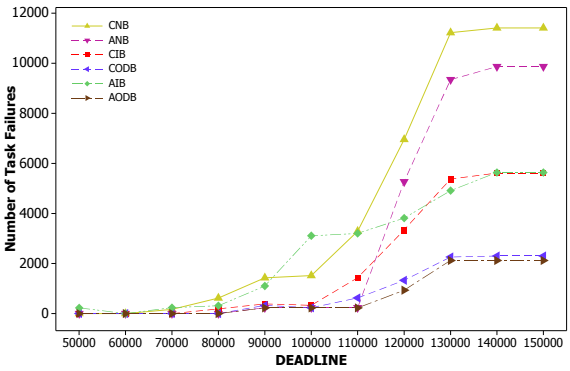

Figure 4.5: Mean of task failures due to bidding strategies.

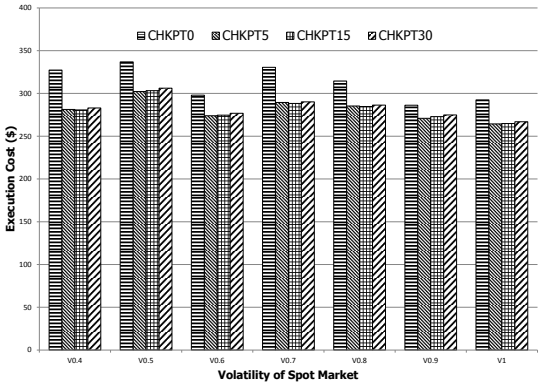

Figure 4.6: Effect of checkpointing on execution cost.

also saves redundant computing reducing the makespan. Even though the task failures for AIB are higher than AODB as shown in Figure 4.5, it does not violate the deadline. Moreover, it reduces costs due to its dynamic bidding strategy.

Figure 4.5 shows the number of failures for conservative and aggressive algorithms under different bidding strategies. It can be observed that naive bidding strategy has the highest failures. However, as the algorithm is adaptive, the impact of failures is not reflected on the execution time. As the figure shows, failures under strict and moderate deadlines are low as the slack time is less. Failures are high under relaxed deadline as the slack time is high. Experimental results show that there is no deadline violation and the algorithm is able to withstand failures irrespective of the bidding strategy.

Figure 4.6 demonstrates the effectiveness of checkpointing. Here, checkpointing with four different frequencies is used for different volatilities of the spot market. The volatility of the spot market is varied by changing the scale of the inter price time i.e., the time between two spot prices. Time between two consequent price change events is reduced, making the price changes more frequent. This in effect compresses the spot market to a smaller time interval. This makes the peaks in the spot market more frequent increasing the risk of pre-emptions. Four different frequencies of checkpointing are used: no checkpointing (CHKPT0), every 5 minutes (CHKPT5), every 15 minutes (CHKPT15) and 30 minutes (CHKPT30). It can be observed that when there is no checkpointing, the cost of execution is 9-14% higher. CHKPT5 gives better reduction in costs than CHKPT15 and

CHKPT30. It can be observed that the execution cost between the CHKPT5, CHKPT15 and CHKPT30 are comparable without significant difference. This can be attributed to low spot prices, the price history we have considered has 82.7% of price changes below $0.01. Therefore, when the average spot price is higher, we will observe a significant difference. Under the spot market considered, CHKPT30 is better as the overhead is lower than CHKPT5, CHKPT15.

4.7 Summary

In this chapter, two scheduling heuristics that map workflow tasks onto spot and on-demand instance are presented. They minimize the execution cost. They are shown to be robust and fault-tolerant towards out-of-bid failures and performance variations of Cloud instances. A bidding strategy that bids in accordance to the workflow requirements to minimize the cost is also presented. This work also demonstrates the use of checkpointing and offers cost savings up to 14%. Simulation results show that cost reductions of upto 70% are achieved under relaxed deadlines, when SIs are used.

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Chapter 5

Reliable Workflow Execution Using Replication and Spot Instances

Cloud environments offer low-cost computing resources as a subscription-based service. These resources are elastically scalable and dynamically provisioned. Furthermore, cloud providers have also pioneered new pricing models like spot instances that are cost-effective. As a result, scientific workflows are increasingly adopting cloud computing. However, spot instances are terminated when the market price exceeds the users bid price. Likewise, cloud is not a utopian environment. Failures are inevitable in such large complex distributed systems. It is also well studied that cloud resources experience fluctuations in the delivered performance. These challenges make fault-tolerance an important criterion in workflow scheduling. This chapter presents an adaptive, just-in time scheduling algorithm for scientific workflows. This algorithm judiciously uses both spot and on-demand instances to reduce cost and provide fault-tolerance. The proposed scheduling algorithm also consolidates resources to further minimize execution time and cost. Extensive simulations show that the proposed heuristics are fault-tolerant and effective, especially under short deadlines, providing robust schedules with the lowest possible makespan and cost.

5.1 Introduction

ALTHOUGH, scheduling scientific workflows on cloud will immensely reduce cost and makespan. Cloud computing, like any other distributed system, is also prone to resource failures. These failures are generally due to software faults, hardware faults, errors in network, data staging issues, failures due to virtualization, disk errors, power issues and many others. These failures from a workflow application perspective can

be classified into 1) task failures, 2) VM failures, and 3) workflow level failures [67]. Nonetheless, failures are inevitable whilst running a complex application like workflows consisting of thousands of tasks.

Furthermore, cloud resources also experience performance variations because of resource sharing, consolidation and migration among other factors. Performance variation of cloud resources affects the overall execution time (i.e. makespan) of the workflow. It further increases the difficulty to estimate the task execution time accurately. Dejun et al. [44] show that the behavior of multiple "identical" resources vary in performance while serving exactly the same workload. A performance variation of 4% to 16% is observed when cloud resources share network and disk I/O [10].

Most providers provision cloud resources (e.g., Virtual Machines (VMs) instances) on a pay-as-you-go basis (similar to On-Demand instances) charging fixed prices per time unit. However, Amazon, one of the pioneers in this space, started selling idle or unused data center capacity through bidding in an auction-like market as Spot Instances (SI) since December 2009. On-demand and SIs have the same configurations and characteristics. Nonetheless, SIs offers cloud users reduction in costs of up to 70% for multiple applications like bag-of-tasks, web services and MapReduce workflows [105, 112, 140]. Significant cost reductions are achieved due to lower QoS, which makes SIs less reliable and prone to out-of-bid failures. This introduces a new aspect of reliability into the SLAs and the existing trade-offs making it challenging for cloud users [71].

These challenges emphasize the necessity for an effective fault-tolerant and robust workflow scheduling algorithm to mitigate resource failures and performance variations. Scientific workflows can also benefit from SIs with an effective bidding and an efficient fault-tolerant mechanism. Such a mechanism can tolerate out-of-bid failures and further reduce the cost immensely.

Therefore, in this chapter we present a just in-time, fault-tolerant and adaptive scheduling heuristic. It uses spot and on-demand instances to schedule workflow tasks. It minimizes the execution cost of the workflow and at the same time provides a robust schedule that satisfies the deadline constraint.

The **key contributions** of this chapter are: 1) A just in-time scheduling heuristic that

uses spot and on-demand resources to schedule workflow tasks in a robust manner. 2) A replication strategy for cloud environments that utilize different pricing models offered by clouds.

5.2 Related Work

Cloud resources experience failures and performance variations that demand fault-tolerance in a schedule. Studies [44,104] have shown that performance of VMs in a cloud environment exhibits variability, and it varies for different instance types, different availability zone, different data centers and different time of the day. Mao et al. [94] have shown that there is significant variation in VM start up time, and it varies with size, OS, and type of instance. They also show that up to 8% of VMs fail while they are acquired. Failures in a distributed system are inevitable and they occur at multiple sources. Failures occur in any of the following levels: hardware, operating system, middleware, network, storage, and task or at the user level. Some of the most common reasons for failure are low memory or disk space, network congestion, unavailability of input files at the right moment, non-responding services, errors in file staging, authentication, uncaught exception, missing libraries, task crashes and many more [110]. Li et al. [86] emphasize the need for fault-tolerance in workflow applications on a cloud environment. Prominent fault-tolerant techniques that can mitigate failures are retry, alternate resource, checkpointing, and replication [25, 148]. In essence, redundancy is fundamental in providing fault-tolerance and it is mainly in two forms: space and time [59].

Redundancy in space is one of the widely used mechanisms for providing fault-tolerance. Redundancy in space is achieved by proving duplication or replication of resources. There are broadly two variants in this approach, task duplication and data replication.

Task duplication creates replica of tasks. Replication of tasks can be done concurrently [31], where all the replicas of a particular task start executing simultaneously. When tasks are replicated concurrently, the child tasks start its execution depending on the schedule type.

Schedules are of two types, first, where the child task starts only when all the replicas have finished execution [12]. In the other schedule type, the child tasks start execution as soon as one of the replica finishes execution [31].

Replication of task is also done in a backup mode, where the replicated task is activated when the primary task fails [100]. This technique is similar to retry or redundancy in time. However, here they employ a backup overloading technique, which schedules the backups for multiple tasks in the same time period to effectively utilize the processor time.

Duplication is employed to achieve multiple objectives, the most common being fault-tolerance [12, 64, 78, 155]. When one task fails, the redundant task helps in completion of the execution. Additionally, algorithms also employ data duplication where data is replicated and pre-staged, thereby moving data near computation especially in data intensive workflows to improve performance and reliability [27]. Furthermore, estimating task execution time a priori in a distributed environment is arduous. Replicas are used to circumvent this issue using the result of the earliest completed replica. This minimizes the schedule length to achieve hard deadlines [33, 45, 114, 132], as it is effective in handling performance variations [31]. Calheiros et al. [20] replicated tasks in idle time slots to reduce the schedule length. These replicas also increase resource utilization without any extra cost.

Task duplication is achieved by replicating tasks in either idle cycles [20] of the resources or exclusively on new resources. Some schedules use a hybrid approach replicating tasks in both idle cycles and new resources. Idle cycles are those slots in the resource usage time period where the resources are unused by the application. Schedules that replicate in these idle cycles profile resources to find unused time slot and replicate tasks in those slots. This approach achieves benefits of task duplication and simultaneously minimizes monetary costs. In most cases, these idle slots might not be sufficient to achieve the needed objective. Hence, many algorithms place their task replicas on new resources. These algorithms trade off resource costs to their objectives.

There is significant body of work in this area encompassing platforms like cluster, grids, and clouds [12, 18, 33, 45, 64, 78, 114, 132, 155]. Resources considered can either be

bounded or unbounded depending on the platform and the technique. Algorithms with bounded resources consider a limited set of resources. Similarly, an unlimited number of resources are assumed in an unbounded system environment. Resource types used can either be homogeneous or heterogeneous in nature. Darbha et al. [33] is one of the early works, which presents an enhanced search and duplication based scheduling algorithm (SDBS) that takes into account the variable task execution time. They consider a distributed system with homogeneous resources and assume an unbounded number of processors in their system.

Resubmission and task redundancy are the most prominent fault-tolerant strategy amongst workflow management systems [110]. They resolve most failures mentioned above in a distributed environment like the cloud. In this work, we employ both redundancy in space and time. We use task replication and task retry to achieve fault-tolerance, to minimize makespan, and also to maximize resource utilization. Here, the proposed algorithm replicates tasks both on idle slots as well as on new resources. Our proposed system model uses an unbounded number of processors, which are heterogeneous in character.

5.3 Background

In this section, we define the important concept of Essential Critical Tasks and metrics that will be further referred in the text. The other essential concepts about workflow, makespan, critical path, latest time to on-demand, pricing models, total cost are defined in Section 4.3 of Chapter 4.

Additionally, in this section we present the problem statement and the assumptions for the research question considered.

Essentially Critical Tasks ($ESCT$). It is important to define the notion of Earliest Finish Time, (EFT) and the Latest Finish Time, LFT to explain $ESCTs$. To explain the concept of EFT we introduce Earliest Start Time, (EST), which is the earliest time a task

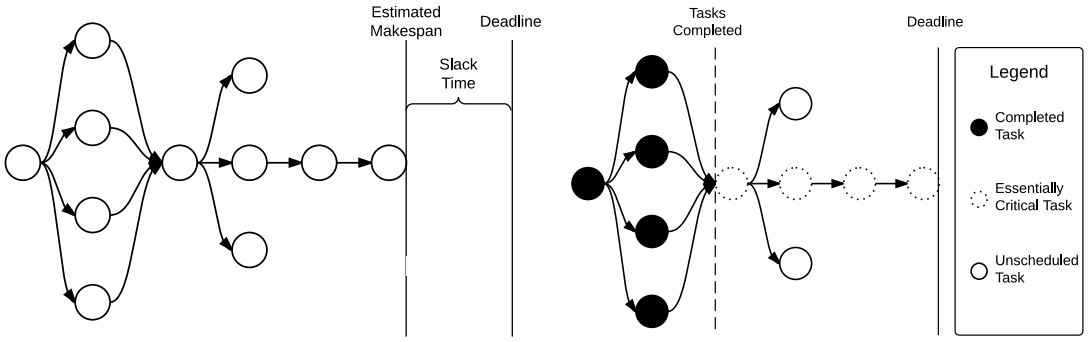

Figure 5.1: Figure(a) shows a workflow at time t_0, where there is enough slack time. Under such situation the tasks are scheduled onto spot instances. Figure(b) shows a workflow at time t_1, where there is no slack time. It also shows some completed tasks. Under such situation, ESCTs are scheduled onto on-demand instances and replicated on spot instances. Other tasks with slack time are scheduled on spot instances.

can start, given by the equation 5.1 [5],

$$\begin{aligned} EST(t_{start}) &= 0. \\ EST(t_i) &= \max_{t_p \in pred(t_i)} \{EST(t_p) + MT(t_p) + c_{p,i}\}, \end{aligned} \tag{5.1}$$

where, $MT(t_p)$ is the Minimum Execution Time of t_p on any instance type. This leads to the definition of Earliest Finish Time, (EFT), which is the earliest a task can finish its execution and is determined by the equation 5.2 [5].

$$EFT(t_i) = EST(t_i) + MT(t_i). \tag{5.2}$$

Finally, Latest Finish Time, LFT, is the latest time a task has to finish execution so that the deadline constraint is not violated. It is described by the equation 5.3 [5]

$$\begin{aligned} LFT(t_{exit}) &= D. \\ LFT(t_i) &= \min_{t_s \in succ(t_i)} \{LFT(t_s) - MT(t_s) - c_{i,s}\}, \end{aligned} \tag{5.3}$$

where, $succ(t_i)$ is all the children nodes of t_i.

Hitherto, Essentially Critical Tasks are the tasks that have no slack time to finish their

execution, i.e., if the $EFT(t_i) \geq LFT(t_i)$ then the task is an $ESCT$. In other words, $ESCT$ is not just a task on the critical path but a task which does not have any slack time and must finish by their EFT, this is shown diagrammatically in Figure 5.1(b). The algorithm schedules *ESCTs* on instances that offer low execution time to avoid *ESCTs* further in the workflow execution.

Two **metrics** are used in this chapter to measure the **robustness** of a schedule 1) *failure probability*, R_p, and 2) *tolerance time*, R_t. The details are presented in Section 3.3 with equations 3.2 and 3.3, respectively.

Replication Factor is the ratio of the total number of replicas created to the number of workflow tasks. This gives an estimate about the number of replicas created for a workflow with a known number of tasks.

The **problem** we address in this work is to find a mapping of workflow tasks onto heterogeneous VM types, using a mixture of on-demand and SIs such that the cost of workflow execution is minimized within the deadline. The schedule should also be robust against resource failures including premature termination of SIs and performance variations of the resources.

Assumptions: Data transfer cost between VMs are considered to be zero, as in most public clouds, data transfer inside a cloud data center is free. The data center is assumed to have sufficient resources, avoiding VM rejections due to resource contention. This is not a prohibitive assumption as the resources required are much smaller than the data center capacity.

5.4 Proposed Approaches

Replication is the most widely used mechanism for enhancing availability and reliability of services. Replication can be done either in space (task duplication) or time (task resubmission). The rationale behind task duplication with n number of replicas is that it can tolerate (n-1) failures without affecting the makespan of the workflow. The downside of task duplication is consumption of extra resources. Task resubmission or retry is an effective fault tolerant strategy where tasks are resubmitted onto a new resource only

when resources fail, hence, it is cost effective although it increases the makespan of the workflow.

In this chapter, the proposed heuristic employs both these fault tolerant mechanisms. When the deadline is short, it employs task duplication, and as the deadlines becomes lenient, it employs task retry to mitigate failures. The working of this heuristic is depicted in the Figure 5.1. The proposed heuristics are detailed in the next subsection.

5.4.1 Heuristics

Scheduling workflow tasks onto heterogeneous VMs is an NP-Complete problem [73]. Hence, we propose an adaptive, just-in-time heuristic. The task dispatcher dispatches ready tasks to the scheduler. It monitors the execution of tasks and resubmits the task if it fails, or submits the child task when all its parent tasks have completed execution. The scheduler maps these ready tasks onto the best suitable resource, such that cost and makespan is minimized and the schedule is fault tolerant. We detail the working of the proposed heuristics in this section.

Once the scheduler receives a task from the task dispatcher, it estimates the critical path. The critical path will potentially be different for every instance type used to estimate it. Therefore, after a task completes its execution, its critical path weight is made zero and for every ready task the critical path time is recomputed. Based on the deadline and the estimated critical path time, the time flag LTO is computed. The difference between LTO and the current time dictates the type of resource and the pricing model that will be selected.

The heuristic acts based on the position of the time flag LTO with respect to the current time. We explain the heuristics presented in Algorithm 5 in four possible scenarios. Scenario 1 and 2 are when LTO is ahead of the current time connoting sufficient slack time to complete workflow execution before the deadline. Under such circumstances, tasks are mapped to spot instances. Scenario 1 illustrates the task mapping onto running instances to consolidate resource usage reducing cost and time. In scenario 2 tasks are mapped onto new spot instances, when no suitable running instance was found. On the other hand, in scenario 3 and 4, when the LTO is before the current time, then the algo-

Algorithm 4: FindFreeSlot(t,vms)

```
   input  : task t, InstanceList, PriceModel P
   output: Suitable VM
 1 types ← available instance types;
 2 estimates ← compute estimated runtime of task t_i on each type ∈ types;
 3 minComplTime ← MaxValue;
 4 for ∀v ∈ InstanceList do
 5     if P = ANY or v.pricemodel = P then
 6         ERT ← estimates(t_v);
 7         GT ← MET − EIT;
 8         ECT ← D − CPT − ERT;
 9         if EIT ≤ MST and ERT ≤ GT then
10             TCT ← EIT + ERT;
11             if TCT < ECT and TCT < minComplTime then
12                 minComplTime ← TCT;
13                 suitableVM ← v;
14 return suitableVM;
```

rithm has to choose expensive and high performing machine to speed up the execution to meet the deadline. Here, tasks are duplicated to provide fault-tolerance as there is no slack time. Replication is done on spot instances to save cost. Hitherto, fault tolerance is achieved by replication. Tasks are either replicated in time or in space based on the deadline, LTO, and the current time.

Scenario 1: Mapping Task on Already Running Spot Instances

First, let us consider the case in which the LTO is conveniently ahead of the current time. In such a case, the algorithm first tries to map the tasks onto spot instances as they are cheap and even if they fail due to out-of-bid events, there is enough slack time to rerun them. Before mapping onto spot instances the heuristic searches for free slots among the resources already in use. If no free slot is found, the scheduler searches for resources, which are running and can finish execution within the task's latest finish time. The latest finish time is the time beyond which if any delay occurs it will violate the workflow deadline.

Free slots are unused idle time periods in instances before the end of their charged

time period. Algorithm 4 describes the methodology of finding these free slots. This method explores only among the specified instances of a particular price model stated by the function call. Here, for every instance in use, the time it will become idle is estimated i.e., expected idle time, EIT. Further, gratis time, GT is computed, which is the difference between EIT and the end time, MET, until which the machine is leased. This gives an estimate of the available idle time in that resource. Furthermore, estimated completion time (ECT) and max start time (MST) for the task is estimated. Estimated completion time (ECT) is computed as shown in line 8 of Algorithm 4, where ERT is the estimated task run time on that instance type and CPT is the critical path time, which is the time taken on the slowest instance. Estimated completion time is a virtual task deadline indicating that the task has to finish within this time to avoid any delay. Hence, the task has to complete its execution before ECT. If the conditions $EIT \leq MST$ and $ERT < GT$ are met, then task completion time, TCT is computed as shown in line 10. Finally, the suitable instance is selected if the TCT on that instance is less than the ECT and its TCT is the minimum among all considered instances.

In the event when no free slots are found, the algorithm finds a suitable running instance which can be used instead of starting a new instance. The rationale being that such instances are readily available, saving boot time. The method $FindRunningVM$ is very similar to the method $FindFreeSlot$, the prominent difference being in the line 9 of Algorithm 4, where the condition $ERT \leq GT$ is omitted. In other words, the algorithm does not validate if the estimated task run time is less than or equal to the gratis time.

Scenario 2: Mapping Task on a New Spot Instance

When no running instance has either a free slot or is capable of honoring the deadline, the heuristic investigates further and checks whether there is sufficient time to run on a new spot instance. If so, the bid price is estimated using a bidding strategy, then the failure probability for that bid price is estimated. Here, **Intelligent Bidding Strategy** is used to estimate bid prices, which was proposed in Chapter 4. This strategy takes into account the current spot price (p_{spot}), on-demand price (p_{OD}), LTO, failure probability (FP) of the previous bid price, the current time (CT), α and β. α, as shown in Section 4.5.2

Algorithm 5: Schedule(t)

input : task t_i

```
/* Variable Initializations                                    */
```

1 *vms* ← all VMs currently in the pool;
2 *types* ← available instance types;
3 *estimates* ← compute estimated runtime of task t_i on each *type* ∈ *types*;
4 *decisionList* ← null;
5 Recompute *CP* and *LTO*.
6 $timeLeft = LTO - currentTime$
7 **if** *timeLeft* > *0* **then** `// If there is sufficient slack time, then find a running instance`
8 *decision* ← **FindFreeSlot**(t_i, *vms*, PriceModel.ANY);
9 **if** *decision.allocated* = *true* **then** *decisionList.add(decision)*;
10 **if** *decision.allocated* = *false* **then**
11 *decision* ← **FindRunningVM**(t_i, *vms*, PriceModel.ANY);
12 **if** *decision.allocated* = *true* **then** *decisionList.add(decision)*;
13 $timeLeft = timeLeft - vmInitTime$
14 **if** *timeLeft* > *0* **then** `// Initialize a new spot instance as no running instance was found`
15 *bid* ← **EstimateBidPrice**(t_i, *type*);
16 **if** *bid* > *on-demand price* **then**
17 Map to on-demand instance and *decisionList.add(decision)*.
18 *failProb* ← **EstimateFailureProbability**(*bid*);
19 **if** *failProb* < *threshold* **then**
20 Map to spot instance and *decisionList.add(decision)*;
21 *InstanceList* ← **FindSuitableInstances**(*CP*, *D*) ; `// Find Instance types that can honor the deadline`

```
/* Finding on-demand instances as sufficient slack time is
   not available                                              */
```

22 *decision* ← **FindFreeSpace**(t_i, *InstanceList*, PriceModel.ONDEMAND);
23 **if** *decision.allocated* = *true* **then** *decisionList.add(decision)*;
24 **if** *decision.allocated* = *false* **then**
25 *decision* ← **FindRunningVM**(t_i, *InstanceList*, PriceModel.ONDEMAND);
26 **if** *decision.allocated* = *true* **then** *decisionList.add(decision)*;
27 *decision* ← **FindCostPerfEffectiveVM**(t_i, *InstanceList*); `// Finding an appropriate new on-demand instance`
28 ...

Algorithm 5: Schedule(t) - Part Two

```
29 compute EFT and LFT for task t_i
30 if Number of Replicas of t_i ≤ 1 then        /* Task Duplication under short
   deadline */
31     if EFT + VMinitTime ≥ LFT then
32         unusedInstance ← instances not used to map replicas of T_i
33         repDecision ← FindFreeSpace(t_i, unusedInstance, PriceModel.ANY);
34         if repDecision.allocated = true then decisionList.add(repDecision);
35         if repDecision.allocated = false then
36             repDecision ← FindRunningVM(t_i, unusedInstance, PriceModel.ANY);
37             if repDecision.allocated = true then decisionList.add(repDecision);
38         if null = repDecision then
39             InstanceList ← FindSuitableInstances(CP, D)
40             InstanceType ← FindCostPerfEffectiveVM(t_i, InstanceList);
41             bid ← EstimateBidPrice(t_i, InstanceType);
42             if bid > on-demand price then
43                 Map to on-demand instance and decisionList.add(repDecision).
44             Map to spot instance and decisionList.add(repDecision);
45 return decisionList;
```

with Equation 4.3. This equation dictates how much higher the bid value must be above the current spot price. Lower the value of α, higher is the value of the bid with respect to the spot price. β determines how fast the bid value reaches the on-demand price. The increase in bid price closer to the on-demand price as the CT reaches closer to the LTO is attributed to the parameter β. The higher value of β, the faster the bid reaches closer to on-demand price. FP of the previous bid is used as a feedback to the current bid price, the current bid price varies in accordance to the FP adding intelligence to the bidding strategy. The bid price is calculated as per the Equation 4.3. The bid value increases gradually with the workflow execution and as the CT moves closer to the LTO. The bid starts around the initial spot price and ends closer to the on-demand price. The rationale of increasing the bid price is to lower the risk of out-of-bid events as the execution nears the LTO making sure that the deadline constraint is not violated. Figure 4.2 shows the working on this bidding strategy with spot price varying with time. It also shows that the bid value steeps up towards the end to reach closer to the on-demand price. The bidding strategy considers all these factors and calculates a bid value in accordance to

the situation.

Scenario 3: Mapping Task to an On-Demand Instance

Let us now examine the case where LTO is behind the current time i.e. there is no slack time, or the estimated bid price is higher than the on-demand price, or the failure probability is higher than the threshold. In such cases the algorithm tries to find a suitable on-demand instance, as on-demand instances have higher QoS guarantees. Before finding an instance, a list of suitable instance types that can honor the deadline are found as shown in Algorithm 6.

In this method **Find Suitable Instances**, critical tasks are determined for every instance type. Ideally, the critical path can vary for different instance types and so does the tasks on it. In other words, tasks have different run times on different instance types and therefore, critical path will also change based on the instance type used to estimate it. Hence, this method evaluates the critical path per instance type and maintains a list of critical tasks per instance type. This computation is done initially and when a task finishes execution, the task dispatcher checks whether the task was critical. If it was, then the critical path for those instance types (i.e. where the completed task was critical) are recomputed. This increases efficiency and avoid computing critical path for every task mapping. Once the critical path tasks are computed, the lines 7- 12 adds the task run time, the transfer time for all the tasks on the critical path. Finally, the total critical path time is computed and if this is less than the remaining deadline, then the instance type is added into the eligible instance list.

This instance list is a list of instance types that can comply with the deadline constraint. Akin to scenario 1, the algorithm first tries to find a free slot among the instance list, if no free slot is found, then an instance is found among the running instances that can execute the task without delaying the deadline. If no instances are found, then $FindCostPerfEffectiveVM$ method calculates the cost of the estimated critical path times with their respective on-demand prices. The instance that can execute with the lowest cost is selected. The algorithm does not select an instance type with lowest price; it selects an instance whose price to performance ratio is the lowest.

Algorithm 6: FindSuitableInstances(estimates)

```
   input  : estimates
   output: Eligible Instance List
 1 types ← available instance types;
 2 InstanceList ← null
 3 for ∀i ∈ InstanceTypes do
 4     CPTasks ← computeCPTasks(i);
 5     prevTask ← null;
 6     CPTime ← 0;
 7     for ∀t ∈ CPTasks do
 8         if prevTask ≠ null then
 9             edgeTime ← edgeTime(prevTask, t);
10         CPTime+ = estimates(t) + edgeTime;
11         prevTime ← t;
12     totalCPTime = CPTime + VMInitTime;
13     if totalCPTime ≤ D − currenttime then
14         InstanceList.add(i);
15 return InstanceList;
```

Scenario 4: Task Duplication Under Short Deadline

Critical tasks are replicated to provide fault tolerance when the deadline is short. We propose two variants of this heuristic. The two heuristics are very similar, with the difference being the tasks they replicate.

Essential Critical Path Task Replication (ECPTR) heuristic: The algorithm 5 details its working. Here, when the LTO has passed the current time, and the task has no slack time, then a replica is created. In other words, all ESCTs are replicated. Similar to the scenarios presented before, first free slots are found among the instances that have not been used to map the replicas of the task considered. If no free slots are found, then a running instance is found that can be used to the map the task without violating the deadline. When neither free slots nor running instances are found, the heuristic maps the replica onto a spot instance. The type of spot instance is decided by methods $FindSuitableInstances$ and $FindCostPerfEffectiveVM$ as shown in lines 39 to 40. Finally, using the bidding strategy, a bid price is estimated for the spot price and if this bid price is less than the on-demand price then a spot instance is instantiated mapping the replica

task.

Furthermore, when a resource fails, the tasks on the resource are resubmitted as ready tasks to the scheduler. In such a case, the task duplication is done only when the number of replicas of the task is zero or one as shown in line 30. In other words, we do not have more than one replica at any particular time for a given task. When the execution of the task finishes, all the replicas are terminated, so that the resources can be freed to accommodate other tasks.

The other heuristic is **Critical Task Replication (CTR**). Here, all the critical tasks are replicated, i.e. once the LTO has moved passed the current time then all tasks are replicated. The replicated tasks are mapped to spot instances to minimize cost. This heuristic is very similar to Algorithm 5, the only difference being, the validation in line 31 is omitted in this heuristic. In other words, under short deadline all tasks will be replicated, although only one replica will be created for a given task at anytime.

5.4.2 Time Complexity

The time complexity for calculating the critical path and re-computing the same for all ready tasks is $O(n^2)$ in the worst case, where n is the number of tasks. The complexity of algorithm for finding a suitable instance for every task is $O(n)$. The complexity of finding the suitable instance depends on the number of instances considered, which is negligible. Hence, the asymptotic time complexity of the algorithm is $O(n^2)$.

5.5 Performance Evaluation

5.5.1 Simulation Setup

We used CloudSim [21] to simulate the cloud environment. It was extended to support workflow applications. It was also extended to model the Amazon spot market. It uses Amazon spot market traces to simulate spot prices.

Application Modeling: The Laser Interferometer Gravitational Wave Observatory (LIGO) workflow with size of 1000 tasks was considered. Its characteristics are explained

Table 5.1: Spot instance characteristics for US west region (North California AZ)

Instance	Average	St Dev	Max	Min	Peaks
m1.small	0.063283	0.055774	0.24	0.0071	570
m1.medium	0.008131	7.30E-05	0.0085	0.008	0
m1.large	0.0163	5.79E-04	0.025	0.016	0
m1.xlarge	0.229384	0.478334	1.92	0.0322	132
m2.xlarge	0.042649	0.116727	1.07	0.0161	18
m2.2xlarge	0.089227	0.204482	2.45	0.0321	48
m2.4xlarge	0.115971	0.160712	2	0.0645	2
m3.xlarge	1.37942	1.763904	6	0.5	167
m3.2xlarge	1.495879	0.544046	2	0.064	64

in detail by Juve et al. [74]. This workflow covers all the basic components such as, pipeline, data aggregation, data distribution and data redistribution.

Resource Modeling: A cloud model with a single data center is considered. The VMs/cloud resources are modeled similar to Amazon EC2 instances. We have considered 9 instance types (m1.small, m1.medium, m1.large, m1.xlarge, m3.xlarge, m3.2xlarge, m2.xlarge, m2.2xlarge, m2.4xlarge) for on-demand instances and SIs. The prices of on-demand instances are adapted from the Linux based instances of Amazon EC2 US West region (North California availability zone). The spot price history is taken from the same region from the period of June 2014 - September 2014. The characteristics of the spot prices for all instances are given in the Table 5.1. Here, we have reported the average spot price, standard deviation (St Dev), minimum and maximum spot prices for the period considered and also the peaks, which is the number of times the spot price was higher than its on-demand price. A charging period of 60 minutes is considered. A boot/startup time of 100 seconds is considered for each instance [94].

Failure Modeling: Failures are modeled by Weibull distribution similar to many other prominent works [68, 70, 81, 90, 110, 131, 147]. We assume these resources to be fail-stop processors, implying that after a failure the resource does not become available again. Further, the failures are considered to be independent. The distribution models the time to failure for a particular resource. The parameters of the Weibull distribution

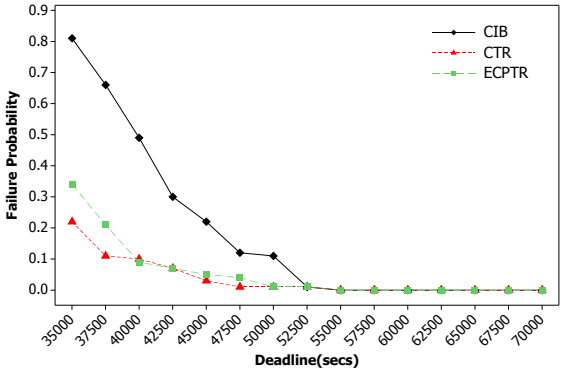

Figure 5.2: Failure probability of algorithms with varying deadline.

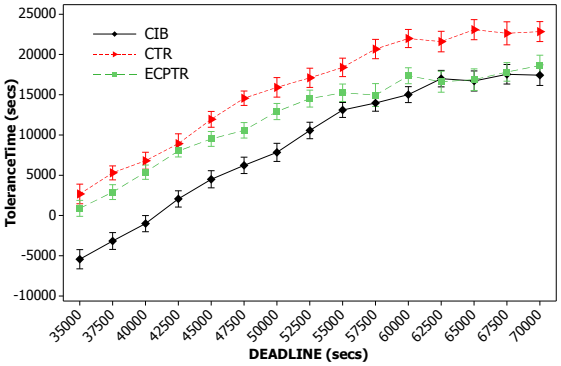

Figure 5.3: Tolerance time of algorithms with varying deadline (with 95% confidence interval).

are modeled similar to the parameters used in [70].

Baseline Algorithms: We compare our heuristics with the ones proposed in [112], which also uses spot instances to reduce cost. This baseline algorithm uses retry as a fault-tolerant mechanism, whereas the proposed solution in this chapter uses both retry and replication. This is one of the few works that uses spot instances for workflow scheduling for fault-tolerance, hence we use this as a baseline for our work. We have also introduced an Essential Critical Path Task Replication without Resource Maximization algorithm (ECPTRRM) similar to ECPTR without resource utilization maximization. This algorithm performs similar to ECPTR but does not place tasks on the same resource maximizing its usage. ECPTRRM demonstrates the effect of maximizing resource utilization on makespan and cost.

5.5.2 Results

In this section, we analyze the performance of our heuristics. We investigate them on the parameters of fault-tolerance, makespan, cost, and resource utilization. Each experiment was run 100 times, with each run starting at a different point in the trace. In other words, for each run we choose a date and time randomly between the start date and end date of the spot market trace to create randomness in the spot prices. We have run for three different combinations of deadline: 1) short deadline (35000 - 45000), 2) moderate (47500

- 57500) and 3) relaxed deadline (60000 - 70000) as shown in the Figures 5.2-5.8. Next, we present results and their analysis on the performance of our heuristics with regards to different parameters.

Fault Tolerance

Providing fault-tolerant schedules is the main objective of this proposed algorithm. Figures 5.2 and 5.3 show the performance of our heuristics with respect to two metrics, failure probability and tolerance time. The details of the metrics were mentioned earlier in section 5.3.

The failure probabilities of the different algorithms are shown in Figure 5.2. It can be observed that under relaxed deadline, all algorithms have substantially lower failure probabilities. When the deadline is short, it can be observed that the heuristics CTR and ECPTR perform considerably better than the baseline CIB. Failure probability of CTR and ECPTR are lower than CIB by 79.75% and 72.36% respectively on average under short deadlines. This is a strong indication that our heuristics have a high probability of success in spite of failures in the environment.

Figure 5.3 depicts the results with respect to the tolerance time. It can be observed that the baseline algorithm CIB has negative tolerance time under short deadlines. This implies that CIB algorithm is not fault-tolerant under short deadline, whereas on the other hand both the proposed heuristics CTR and ECPTR have significantly positive tolerance time. This suggests that they are fault-tolerant and can withstand more failures and performance variations given the same schedule. It is also evident from the figure that ECPTR has a higher tolerance time than CTR and this difference becomes larger as the deadline becomes relaxed. Additionally, the tolerance time of CIB and ECPTR become similar as the deadline is relaxed. This is due to the fact that CIB and ECPTR perform similar to each other under relaxed deadlines.

Effect on Makespan

Makespan is the other important objective that we consider. We attempt to minimize it especially when the deadline is short. Figures 5.4 and 5.5 are presented, showing the

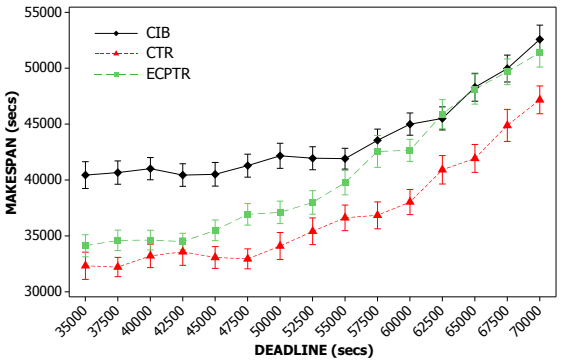

Figure 5.4: Mean makespan of the proposed algorithms against the baseline with varying deadlines (with 95% confidence interval).

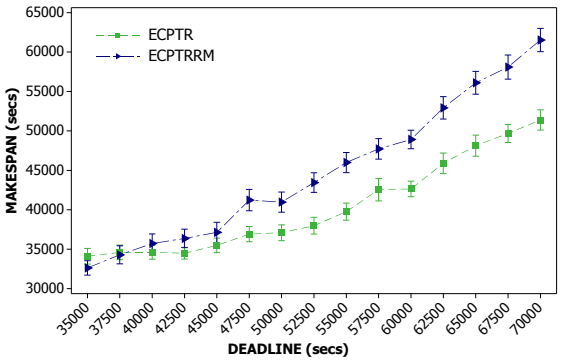

Figure 5.5: Showing the effect of resource consolidation on makespan for ECPTR heuristic (with 95% confidence interval).

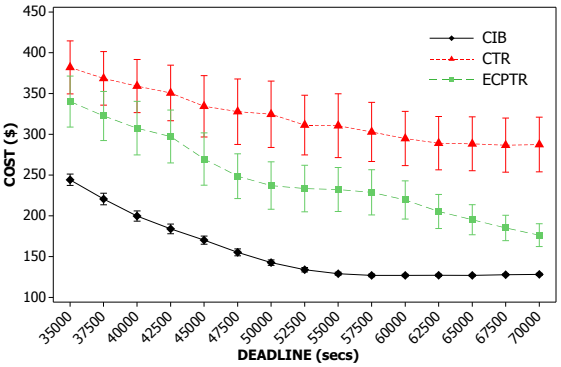

Figure 5.6: Mean execution cost of the proposed algorithms against the baseline with varying deadline (with 95% confidence interval).

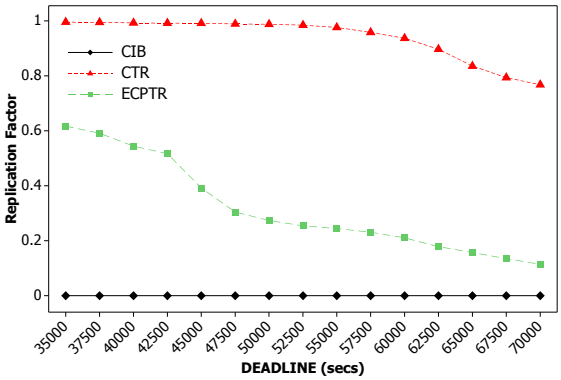

Figure 5.7: Replication factor for the algorithms with varying deadline.

performance of our algorithms with respect to makespan. The working of our algorithms with respect to the baseline algorithm is depicted in Figure 5.4. Additionally, the effect of resource maximization on makespan is shown in Figure 5.5.

The proposed heuristics in comparison with the baseline generate schedules with makespan lower than the baseline. The Figure 5.4 shows the results with a 95% confidence interval. It can be observed from the figure that CTR outperforms both CIB and ECPTR, which is essentially because CTR generates more replicas. Task duplication helps generate effective schedules with lower makespan in spite of failures and performance variations.

ECPTR has makespan lower than CIB by 14.47%, 25.14% and 32.17% respectively when the deadline is short, moderate and relaxed respectively. Similarly, CTR has a makespan lower by 43.43%, 56.44% and 55.95% under short, moderate and relaxed deadlines respectively against CIB algorithm. Furthermore, schedules generated by CTR are 23.93% lower in makespan than ECPTR schedules.

Figure 5.5 shows the results when resource consolidation is considered. The effect on makespan is lower when the deadline is short, the reason being compaction of resource are not possible to a significant extent due to deadline constraints. Whereas, under moderate and relaxed deadlines, ECPTR generates schedules with 11.37% and 14.24% lower makespan respectively, when compared to ECPTRRM. This reinforces that maximizing resource utilization reduces makespan. It reduces data transfer time, and the boot time needed to initialize new instance, by mapping two or more tasks onto the same resource.

These experiments solidify the facts that task duplication and maximizing resource utilization help lower the makespan significantly.

Effect on Cost

Execution cost is the third objective we strive to minimize. The proposed algorithms use a mixture of spot and on-demand instances to reduce cost. Here, spot instances are used for replication when the deadline is tight and spot instances are used as the primary resource when there is sufficient slack time. This dynamic approach makes the best use of the available pricing models to significantly reduce cost. Cost savings when using spot

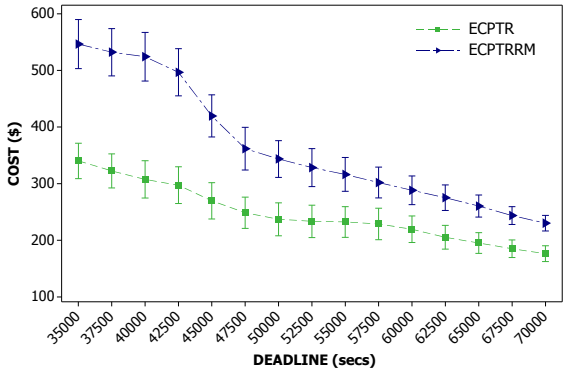

Figure 5.8: Showing the effect of resource consolidation on cost for ECPTR heuristic (with 95% confidence interval).

instances are quantified in the paper [112].

However, in Figure 5.6, the costs of algorithms ECPTR and CTR are higher than the baseline algorithm. This increase is attributed to the replicas these algorithms create. It can be further noticed that the cost of ECPTR is higher than CTR, as ECPTR generates more replicas than CTR. Figure 5.7 shows the number of replicas created by each algorithm for different deadlines. It can also be observed that as the deadline becomes more relaxed, the number of replicas is also reduced and this is more significant for ECPTR heuristic. Similarly, the cost difference between CIB and ECPTR is also reduced as the deadline becomes relaxed.

Apart from the efficient use of pricing models, effective resource usage also reduce costs considerably. Figure 5.8 testifies this, it can be observed here that the cost of ECPTR is much lower than the ECPTRRM algorithm. When tasks are packed into a single resource the costs can be reduced significantly. Figure 5.8 shows that when the deadline is short, execution cost of ECPTR is 38.86% lower than ECPTRRM and it 24.34% lower under relaxed deadlines.

5.6 Summary

Cloud computing offers low-cost computing services as a subscription based service, which are elastically scalable, and dynamically provisioned. Additionally, it offers attractive pricing models like on-demand and spot instances. Because of which scientific

workflow management systems are rapidly moving towards clouds.

However, cloud environments are prone to failures and performance variations among resources. Failures are traditionally mitigated using replication, which increases the execution cost and time. Whereas with innovative pricing models cloud offers, the cost for providing fault-tolerance can be drastically reduced. In this chapter, we have proposed two just-in-time adaptive workflow scheduling heuristics for clouds. These heuristics use on-demand and spot instances to provide fault-tolerant schedules whilst minimizing time and cost. They are fault-tolerant against performance variations, out-of-bid failures and resource failures. Extensive simulations have shown that the proposed heuristics generate schedules with significantly lower failure probabilities. The makespan of these schedules is much lower than the baseline algorithm. These heuristics are also shown to maximize resource utilization. These experiments establish that pricing models offered by cloud providers can be used to reduce costs and makespan and at the same time provide robust and resilient schedules.

Chapter 6

Framework for Reliable Workflow Execution on Multiple Clouds

In this chapter, we extend the Cloudbus workflow management to dynamically provision resources for multiple clouds. The broker is enhanced to provision resources dynamically on the go. Additionally, an effective fault-tolerant technique is developed to retry tasks after failures. Finally, a resource provisioning algorithm to demonstrate the multi-cloud capabilities is proposed and its effectiveness is shown.

6.1 Introduction

SCIENTIFIC workflows are executed with the help of workflow management systems. Workflow management systems take workflows as input, analyze their dependencies and map the workflow tasks on to distributed resources. They also maintain and manage the storage requirements of the workflows.

Diverse areas such as high-energy physics, life sciences, genomics, bioinformatics and astronomy extensively represent their applications as scientific workflows. These are executed on distributed systems to obtains their scientific experimental results. These applications have increasingly adopted cloud environments. These applications can be either compute, or data, or I/O intensive applications.

Most workflow management systems have moved to cloud computing and are benefiting from its pricing models and on-demand dynamic provisioning. However, multiple cloud providers offer clouds resource in an attractive way. An application running in a multi-cloud environment can benefit in more than one way. Pricing is a very impor-

tant factor for moving towards multiple clouds. Different cloud providers price their resources differently. Resource characteristics also vary across cloud providers and a wide choice will benefit the application significantly. A hybrid cloud scenario consisting of public and private clouds, where running on a private cloud is cheaper, but resources are limited. On the other hand, a public cloud has vast amount of resources, but resource cost, data transfer time and cost are involved. To balance cost and workload in such an environment is an interesting case for multiple clouds. Additionally, in a workflow management system capable to provisioning resources on multiple clouds, it is easier to switch between different clouds eliminating the need to integrate multiple API's of different providers. Finally, regulatory and legal issues concerning data location, its privacy and security effect are also addressed by a multi-cloud environment [63].

This chapter presents a workflow management system developed as part of the Cloudbus toolkit at the CLOUDS Lab in the University of Melbourne, Australia [19]. The presented workflow system is a mature system springing from years of research and development. This system deploys various strategies, resource selection and allocation policies in a pluggable manner. It also supports complex control and data dependencies for scientific workflow applications. In this chapter, we first provide an overview of the workflow management system, its architecture, components, and functionalities. Then we introduce the necessity of multi-cloud environments and detail the implementation of the new multi-cloud feature. Further, we test this implementation with a case study of an astronomy application explaining its nature, implementation details and results. Finally, we describe the related works in the area of workflow management systems.

The key contributions of this chapter are: 1) Integrating the Apache jclouds toolkit into the Cloudbus workflow management system. This enables the workflow management system to provision resources on demand and on the fly. It facilitates provisioning of resources on multiple cloud providers. Therefore, the Cloudbus workflow management system can provision resources on a single cloud providers or a combination of cloud providers. 2) We have developed a resource provisioning algorithm for a multi-cloud environment with two kinds of cloud resources. 3) Lastly, a task retry fault-tolerant mechanism is developed to mitigate cloud failures.

6.2 Cloudbus Workflow Management System Architecture

This section presents various components and their relationships with plug-in services of the Cloudbus workflow management system. The architecture of the Cloudbus workflow management system is shown in Figure 6.1.

Workflow management systems facilitate the modeling/composition, submission, execution, and fault, data and provenance management of the workflow. The Cloudbus workflow management system consists of a web portal, a workflow engine and services that support its execution. The workflow execution can be performed either through a web portal or through a standalone application [107].

The **Workflow portal** aids in workflow composition, design and modeling. Workflow applications are specified in an XML-based workflow language called xWFL format. The Workflow portal accepts workflows through a *workflow editor*, or through a workflow specification in xWFL format that will be submitted to the *workflow engine*.

Cloudbus Workflow management system [108] uses xWFL for application composition. This language allows users to define, tasks, data dependencies, QoS constraints, and I/O models. xWFL allows tasks to be defined as a single task or as a parameter sweep task. This provides researchers with the flexibility to perform experiments with a range of parameters. Similarly, data dependencies specify the flow of data between tasks. Alternatively, I/O models explicitly specify the data handling capabilities of each task. Three types of I/O models are supported *many-to-many*, *many-to-one* and *synchronization* [150].

Input data for a task might be generated by multiple tasks. How these input will be processed and when the output will be generated by the task and its sub-tasks determines the I/O model. For instance, many-to-many model start to process data and generate output data as and when the input data is available. Alternatively, many-to-one starts to process data once an input is available but generates output data based on its earlier subjobs. Finally, synchronization model processes data only when all input data is available.

The **workflow engine** accepts the workflow application composed or submitted by the portal. It submits the workflow to the *workflow submission handler*. Once a workflow is submitted to the system the workflow language parser translates it into tasks, dependencies, data objects, exceptions and parameter specifications. The workflow management

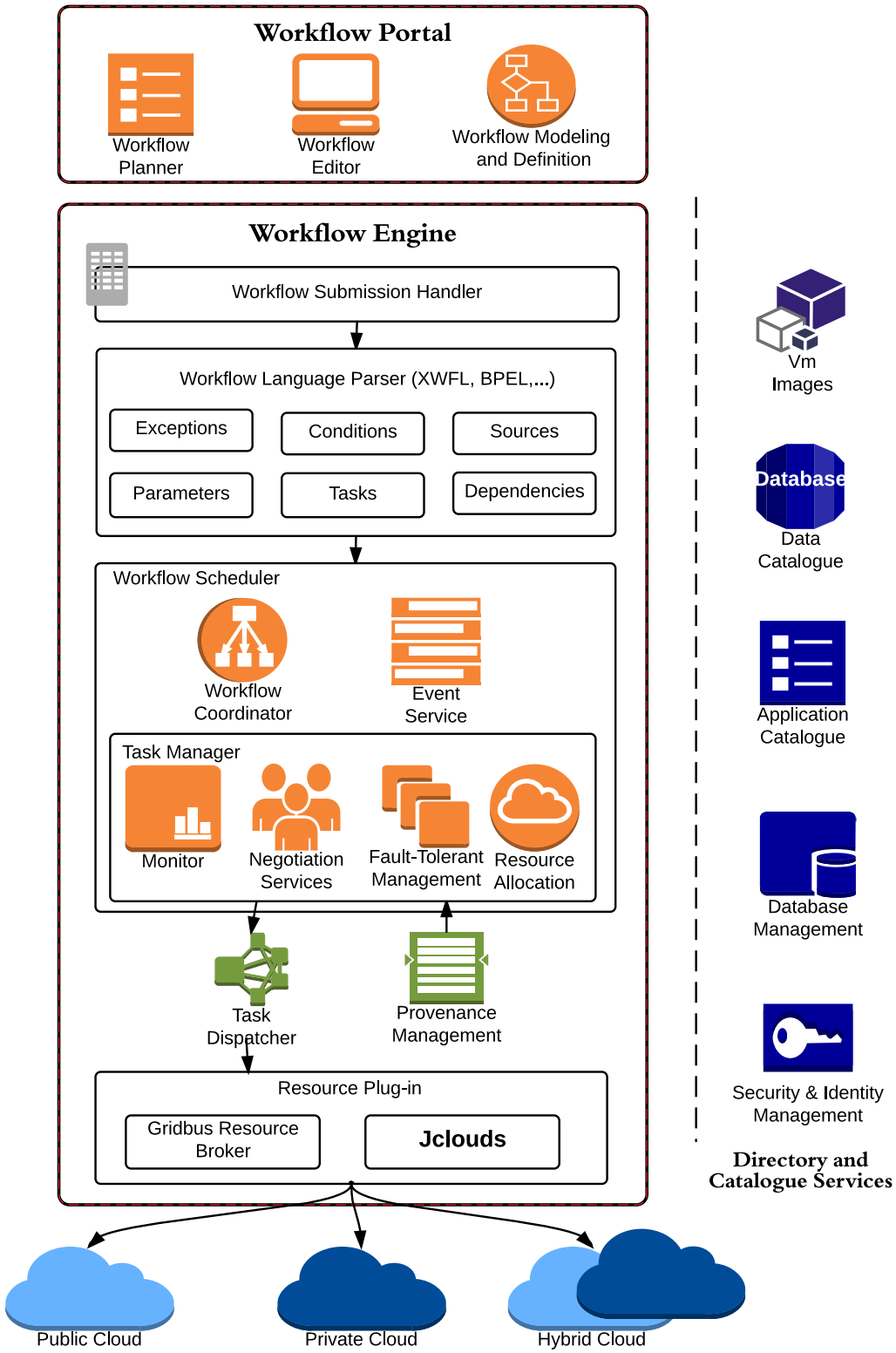

Figure 6.1: Cloudbus workflow management system.

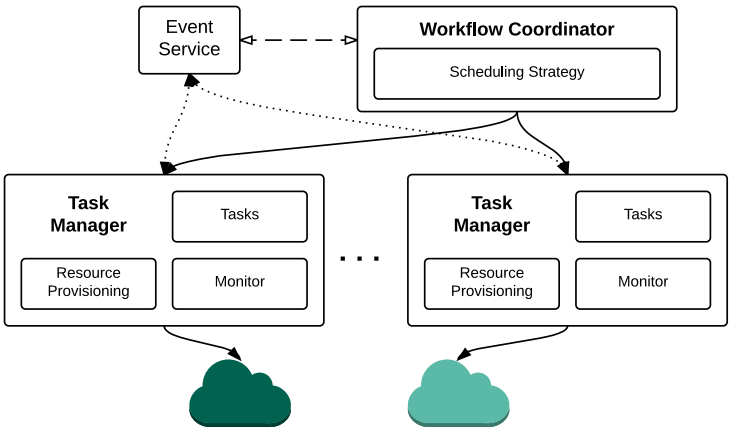

Figure 6.2: Components of workflow scheduling.

system also allows different workflow language parsers to be plugged-in.

These specifications are submitted to the *workflow scheduler* for execution. The workflow scheduling architecture specifies the placement of the scheduler in a WFMS and it can be broadly categorized into three types: *centralized*, *hierarchical*, and *decentralized* [148]. In the *centralized* approach, a centralized scheduler makes all the scheduling decisions for the entire workflow. The drawback of this approach is that it is not scalable; however, it can produce efficient schedules as the centralized scheduler has all the necessary information. In *hierarchical* scheduling, there is a central manager responsible for controlling the workflow execution and assigning the sub-workflows to low-level schedulers. The low-level schedulers map tasks of the sub-workflows assigned by the central manager. In contrast, *decentralized* scheduling has no central controller. It allows tasks to be scheduled by multiple schedulers, each scheduler communicates with each other and schedules a sub-workflow or a task [148]. The Cloudbus workflow management system uses a decentralized scheduling architecture for workflow execution [150].

As shown in Figure 6.2, the execution of workflow is mainly performed by the *Workflow Coordinator*, which is a part of the workflow scheduler in our workflow management system. The workflow coordinator outsources the workflow execution to the *Task Managers* and the *Event Service* providing a decentralized architecture to the workflow management system.

A task manager is created for each task, which can handle the processing of a task,

including resource allocation and discovery, monitoring, negotiation services, and fault-tolerant management. Each task manager employs their own strategies for resource provisioning, SLA and data management. They also have monitors to monitor the task execution status on a cloud resource. As shown in the Figure 6.2, each task has its own task manager.

Additionally, two fault handling techniques are available and they are *retry* and *task replication* [150]. Retry mechanism reschedules a failed job to an available resource. It also records the number of failed jobs for each resource. A warning threshold is set for the number of failed jobs on a particular resource, and if this threshold is exceeded the scheduler decreases the quantum of jobs submitted to this resource. However, if the number of failed jobs exceeds a critical threshold, then the scheduler stops submitting jobs to that resource.

The task replication technique replicates a task on more than one resource. The earliest resource to produce the output is used. These two mechanisms help mitigate failures and performance variations that can be experienced in distributed environments.

To manage the entire workflow execution coherently, there is a necessity for a communication model, as every task manager is an independent and parallel thread for task execution. However, these tasks managers are dependent on other tasks through data and/or control dependencies and these dependencies could be one-to-one or many-to-many.

Event service addresses this requirement by providing an event-driven mechanism with subscription-notification model to control and manage execution activities. This service registers events from tasks managers and notifies the workflow coordinator. Therefore, task managers do not communicate with each other, making the event service a loosely coupled design allowing new and easily pluggable extension into the architecture.

Event services allow three types of events basically: *status event*, *output events* and *control events*. Task managers send status and output events informing about their execution statuses and results. Workflow coordinator sends control events to task managers, such as pause and resume.

Once the workflow scheduler maps a task to a resource, the dispatcher dispatches the tasks to the right middleware. The workflow management system is designed to support multiple middleware and this is done by creating dispatchers for each middleware. The dispatcher supports interaction with resources of a specific kind. Currently, the Cloudbus WFMS supports Aneka, Globus, and fork-based middleware.

Plug-ins supports various services that aid in workflow execution on different environments and platforms. The workflow management system has several plug-ins for:

- Determining task, data, and resources characteristics through metadata information or through trace files.
- Data transfer between broker, resources and storage.
- Monitoring the status of tasks, application, and resources.
- Catalogues services for resources, tasks, and their replicas.

6.3 Multi-Cloud Framework for Cloudbus Workflow Engine

Workflow management systems have migrated in huge numbers from grids to clouds. Multiple large software companies have ventured into the cloud domain offering cloud resources with innovative and attractive pricing and other benefits. To leverage these features from multiple cloud providers, its imperative that existing workflow management system evolve to work in a multi-cloud environment and not be locked in to a single cloud provider.

Advantages of a multi-cloud environment are manifold: 1) *Pricing:* multiple cloud providers offer cloud resources through various pricing models. For example, AWS offer spot instances which are very cheap but have lower SLAs guarantee. Similarly, there are reserved instances, and on-demand instances, and each pricing model has its pros and cons. 2) *Billing Periods:* cloud providers provision cloud resources with different billing periods, for example, AWS bills resources per hour, Google bills per minute. Depending on the workflow task length, choosing the right billing period can increase cost savings significantly. 3) *Resource characteristics:* cloud providers offer resources with different

characteristics with varying RAM, CPU and others, this enables the workflow management system to pick the right configuration for a task based on whether it is compute intensive, data intensive, or I/O intensive. 4) *Private cloud:* many organization and institutes have private clouds, where computation is generally free. However, resources are limited in such an environment and a combination of private and public cloud infrastructures could address these resource limitations. 5) *Regulatory and legal*: issues concerning data location, its privacy and security affect in choosing an appropriate cloud provider [63].

Multi-cloud frameworks address all these issues and help large and complex workflows to execute seamlessly. However, moving to multi-cloud environment has its own challenges. Latency between users and different clouds could impact the application performance largely. Cloud providers do not have similar API's for accessing their cloud infrastructures. Therefore, interoperability is a major issue. Additionally, time and cost of data transfer in and out of cloud data centers is an important challenge.

In this work, we have used an open source toolkit called Apache jclouds to help workflow management system to work with a multi-cloud framework. This toolkit supports most of the major cloud providers available today through a simple API. This toolkit is integrated into our system, which enables it to provision resources dynamically on multiple clouds on the fly effortlessly. In the next section, we detail this toolkit and its integration with our system.

6.4 Apache Jclouds: Supporting Multi-Cloud Architecture

Jclouds is a java-based multi-cloud toolkit developed by the Apache foundation. It is an open source library that provides APIs, which allow portable abstractions for cloud-specific features. jclouds supports 30 cloud providers and cloud software stacks such as, OpenStack, Amazon, Google, Rackspace, and Azure [1].

Among the several API abstractions, the prominent ones are the *BlobStore* and *ComputeService*. BlobStore is a simple and portable way to manage storage providers. It provides a map view of the storage container for accessing data. On the other hand, Com-

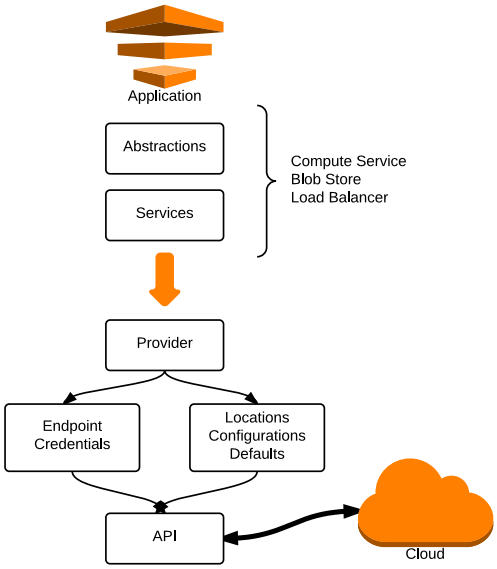

Figure 6.3: Apache jclouds system integration architecture.

puteService provides a simple abstraction to create multiple instances in multiple clouds through simple APIs and further provide convenient methods to install software on these machines. jclouds also provide *Load balancer* API to configure load balancers of any cloud through a common interface [1].

Apache jclouds is an easy to plug toolkit that facilitate multi-cloud features to the application and provide features like high availability, privacy, monetary and performance benefits. It helps existing applications to connect to multiple cloud services seamless through simple layers of abstraction. It provides consistent integration pattern that is essential while managing multi-cloud environment. It offers pluggable components that help in extending the application smoothly; it also assists in error or retry handling. The system integration architecture of jclouds with an arbitrary application is shown in Figure 6.3.

Apache jclouds offers a connection to a provider through a context, which can be done in two ways as shown in the Listings 6.1 and 6.2. The compute service context provides a handle to a cloud provider and it can be used to create a *ComputeService* through which, instances can be created, destroyed, suspended and resumed. ComputeService can also be used to get information about nodes, locations, images, hardware types and keypairs. This shows that jclouds has a rich

set of cloud specific services and it can be used seamlessly in an effortless manner.

Listing 6.1: Context Creation

```
ComputeServiceContext ctx = ContextBuilder.newBuilder("Cloud-Provider")
   .credentials("identity","credential")
   .buildView(ComputeServiceContext.class);
```

Listing 6.2: Context Creation through Endpoint

```
ComputeServiceContext ctx = ContextBuilder.newBuilder("Cloud-Provider")
   .credentials("identity","credential")
   .endpoint("endpoint-url");
   .buildView(ComputeServiceContext.class);
```

6.5 Apache Jclouds and Cloudbus Workflow Management Systems

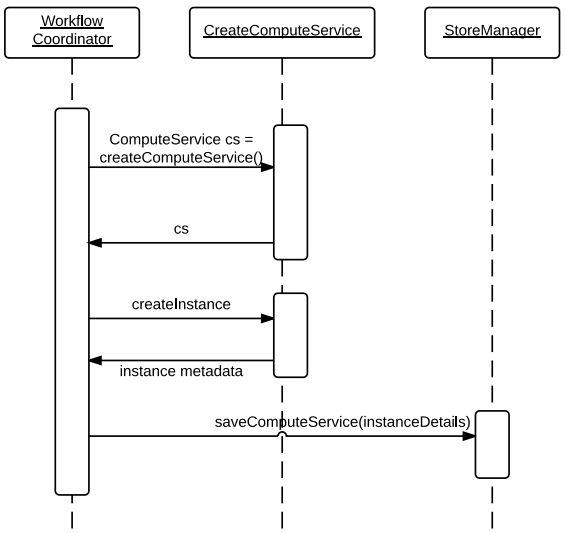

Figure 6.4: Sequence diagram of jclouds integration.

To leverage the advantages of multi-clouds, we have integrated jclouds into our Cloudbus workflow management system. Figures 6.4 and 6.5 illustrate how the jclouds toolkit is plugged into the system. As shown in Figure 6.4, the workflow coordinator

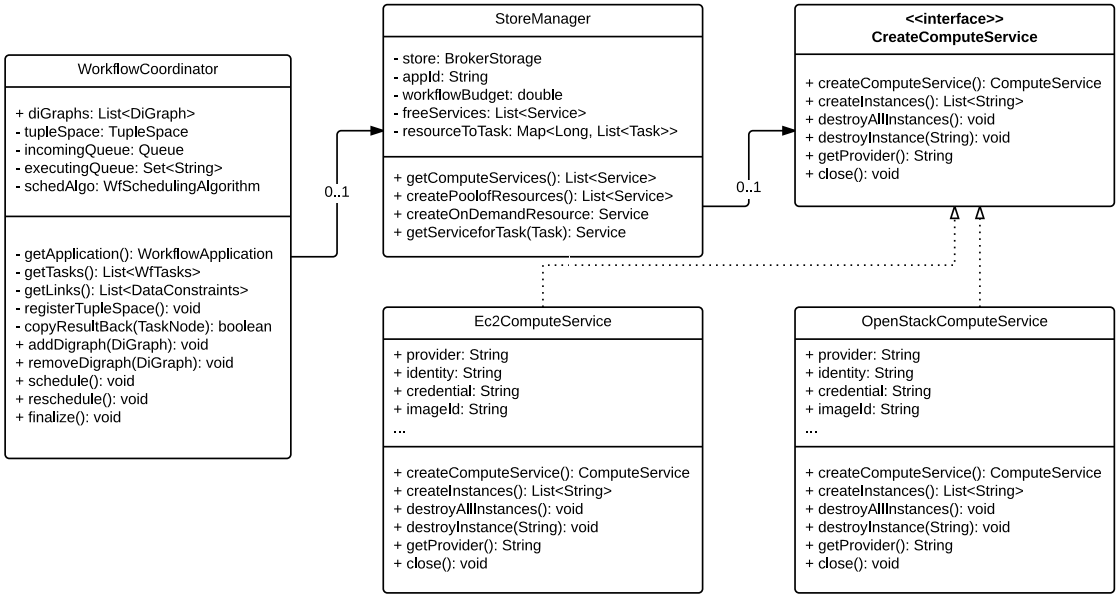

Figure 6.5: Class diagram representing resource provisioning through Apache jclouds.

class interacts with the StoreManager to provision resource. The store manager creates and manages the resource. It also assigns the most suitable resource to a particular task based on the resources capabilities. The next subsection details this resource provisioning heuristic.

The store manager invokes an implementation of the abstract *createComputeService* class depending on the inputs from the workflow coordinator. Through the compute service, class instances of any supported kind can be created using the create instance method. The number of instances that need to be created can also be mentioned and jclouds creates these instances and provides the metadata information. The workflow coordinator further stores these instance details into the database through a store manager.

Task retry is developed in the task manager as a part of the fault-tolerant mechanism. When a task fails due to resource, task, or network failure, the job monitor notifies the tuple space through an event. The task manager of the failed task reads the status and then apply a corrective action. The task manager remaps the failed task to another resource, additionally, the store manager is notified of the failed resource so that no further tasks are mapped to that failed task.

The task manager, before submitting the task to a resource, verifies with the store

manager whether the resource is active or not. This avoids submitting tasks to failed resources, which where scheduled on that resource before it failed.

In the following subsection, we briefly describe the overall algorithm and the proposed multi-cloud resource provisioning heuristic.

6.5.1 Multi-Cloud Resource Provisioning Heuristic

Algorithm 7: FindComputeResource(task)

```
   input  : Task t
   output: Compute Resource
 1 freeResources ← available compute resources;
 2 resourceToTasksMap ← null
   /* Find a free compute resource.                                  */
 3 if freeResources.size() > 0 then
 4     Resource r = freeResources.remove(0);
 5     Add an entry of task t and resource r in resourceToTasksMap,
 6     If r exists add t to r's list of tasks.
 7     return r;
   /* Create new compute resource.                                   */
 8 else if (budget − resourcePricePerHr) ≥ 0 then
 9     Resource r = create on-demand instance;
10     Add an entry of task t and resource r in resourceToTasksMap
11     return r;
   /* Find a suitable and available compute resource.                */
12 else
13     parentsList ← Get list of parent for task t
14     resourceList ← null
15     for ∀resourcer ∈ resourceToTasksMap do
16         if taskList of r is empty then
17             resourceList.add(r);
18         else if taskList contains any task from parentsList then
19             resourceList.add(r);
20     return a resource that can start the earliest from resourceList;
```

The workflow coordinator supports a just-in-time scheduling heuristic. Here, initially the first level tasks or the entry nodes are assigned to a compute resource. Then, as the parent tasks finishes execution and produces the relevant output files, the dependent tasks are made ready for execution [106]. The scheduler assigns an available resource

to these ready tasks through a resource provisioning policy. The workflow coordinator invokes this resource allocation to get a compute resource for the task.

The contribution of this chapter is developing a novel multi-cloud resource provisioning policy that allocates resources from two cloud providers and two types of resources i.e., spot instances and on-demand instances.

The scheduling heuristic is also fault-tolerant. When a failure occurs, the task manager is notified and it reschedules the failed task onto another resource and removes the resource from the resource pool. This ensures that other tasks are not mapped to the failed resource.

The proposed multi-cloud resource allocation policy is outlined in Algorithm 7. Initially, a pool of spot instances are created and assigned to the *freeResources* set. This is done because spot instances take longer time to boot up [94]. The budget is given by the user and the number of on-demand and spot resources created is based on this budget. If the spot-instances go out-of-bid or extend beyond their charging period, the budget is updated accordingly.

The proposed resource allocation policy initially finds a free resource for the given task. On finding a free resource, the *resourceToTasksMap* is updated for book keeping. If multiple free resources are found, the first resource is chosen. If no free resource is found and if there is sufficient budget to create a new on-demand resource, then an on-demand resource is instantiated. If there is no sufficient budget to create new instances, then the resource allocation policy finds the best possible resource from the available resources. The resource allocation policy evaluates all the resources and chooses a resource that is available in the earliest. If possible, it selects a resource that is running a parent task as it reduces the data transfer time. For this reason, the resource allocation policy creates a list of all parents of the given task. It iterates through each resource from the *resourceToTasksMap* adding suitable resources into a *resourceList*. It is a list of all feasible resources. If the resource has no tasks then it is a free resource with no tasks running or scheduled on it, therefore, the resource is added to the resource list. If the resource has tasks, i.e., running or scheduled tasks, then the policy checks whether the running or scheduled tasks contain any of the parents tasks. If it does, then that resource will reduce the data transfer

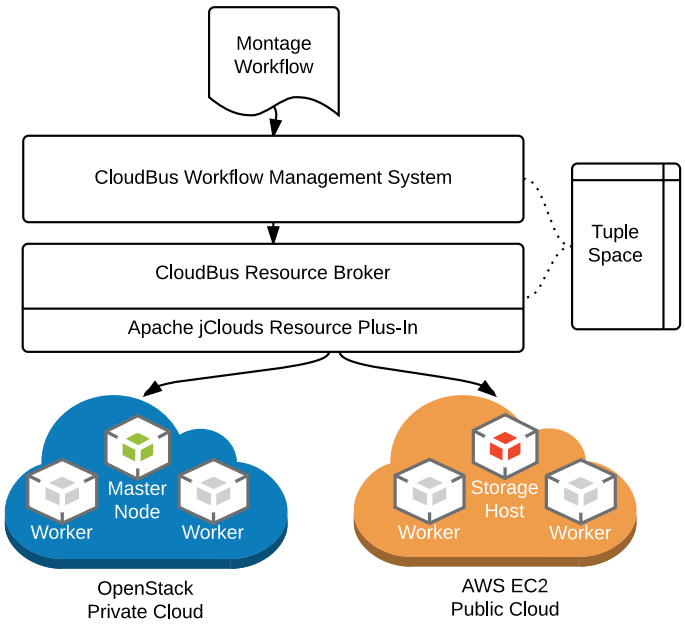

Figure 6.6: Testbed environment setup illustration.

time and it is added on to the resource list. Finally after all the iterations a resource that is available in the earliest is chosen from resource list.

6.6 Testbed Setup

This section provides the implementation details of the Cloudbus workflow management system as shown in Figure 6.6. As pointed out in the earlier section, this system uses IBM TSpaces [145], which provides a loosely-coupled design for an event-driven mechanism with subscription notifications. The components communicate through these events. The application, resource, environment and experiment details are provided below:

6.6.1 Montage: A Case Study of Astronomy Workflow

Astronomy studies celestial bodies and space through image data sets that cover a wide range of electromagnetic spectrum. These images are presented to astronomers in various coordinate systems, variety of map projections, image sizes, pixel densities and spatial samplings. Additionally, more than the individual image, the mosaic of these images

Table 6.1: Description of montage workflow tasks

Component	**Description**
mProjectPP	Produces a re-projected image to the scale defined in the template file and also an 'area' image sky area containing the fractional input pixels
mDiffFit	Image difference for two overlapping images (i.e., pixels line up accurately) is done.
mConcatFit	It is a compute intensive job, which aggregates the data produced from all the mDiffFit jobs.
mBgModel	Achieve a global fit for each image by applying a set of corrections.
mBackground	Image's background is removed.
mImgTbl	Aggregates image metadata and creates a table.
mAdd	Co-adds two re-projected images from the same metadata table, using a common FITS header template
mShrink	FITS image's size is compressed.
mJPEG	JPEG image is created from the shrunken image.
mDiffExec	mOverlaps determines identical pairs and this module executes mDiff on those.
mFitplane	An image is fitted into a plane ignoring its outlier pixels.

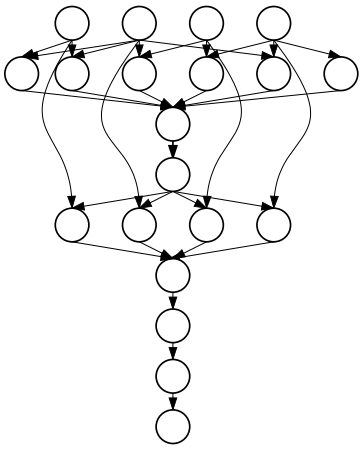

Figure 6.7: Montage workflow.

holds greater importance and significance to astronomers representing significant structures, such as star formations, regions, and cluster of galaxies, etc.

These complexities require comprehensive image mosaic software that meets astronomer's requirements (e.g., coordinates, rotation, size, projections). The Montage software toolkit is designed for this specific requirement. Montage widens astronomical research avenues by enabling mosaic generation through software tools, and it also includes deep source detection by studying wavelength-dependent structures, combining multiple wavelength data, and detecting minuscule features through image differencing.

Montage toolkit was designed to process tasks that compute such mosaics through independent modules using simple executables. This toolkit can be run on desktops, clusters, grids, supercomputers and clouds, and it effectively uses parallel computing environments to scale and speed-up on as many processors as possible.

Montage application [16] is a complex astronomy workflow. We have used a montage workflow consisting of 110 tasks, where the number of the tasks indicates the number of images used. It is a I/O intensive application, which produces a mosaic of astronomic images.

The Architecture of Montage

Montage computes an image mosaic through the following steps:

1 Re-projecting images onto a common coordinate system, spatial scale, and world coordinate system projection.

2 Minimizing the inter-image differences and achieving common flux scales through modeling the background radiation.

3 Rectifying background level and common flux scale of images.

4 Addition of re-projected and corrected images into a final mosaic.

The independent modules of the Montage toolkit that comprise of a workflow are listed with brief description in Table 6.1 and the workflow of montage is depicted in Figure 6.7.

6.6.2 Resource Characteristics

Workflow management system requires three kinds of resources:

- Master Node: this is where the portal, engine and the resource broker is hosted. This node was hosted in the OpenStack private cloud.
- Storage Host: this node hosts all the data, input, output, and the intermediate files. The node was in the Amazon AWS Sydney region.
- Worker Node: this node performs the workflow execution. It could be created either in the OpenStack cloud or the Amazon AWS cloud.

Resources communicate with each other through password-less SSH. The configurations for this where made in the cloud resources respectively.

6.6.3 Environment

We have used two cloud environments. We have used an OpenStack private cloud deployed in The University of Melbourne. The OpenStack environment is setup on three IBM X3500 M4 servers, each with 12 cores (2 x Intel Xeon 2.0GHz Processor , 15MB Cache)

with 2.1 TB disk space and 64GB RAM. Instance of m1.tiny where used for worker nodes. M2.4xlarge was used for the master node.

The second cloud we have considered is the Amazon EC2 cloud. We have considered the Asia Pacific (Sydney) region as it is the closest to us and will have the minimum latency. T1.Micro instances where used for worker and storage nodes in the public cloud.

6.6.4 Failure Model

Resource failures was orchestrated to demonstrate the fault-tolerance of the workflow management system. mProjectPP and mBackground tasks types where choosen to be failed, as they are higher in number and they affect two levels of workflow execution. The workflow variant we have choosen has 25 tasks each of these types. Failing any of these task impacts the execution similarly. Three from each of these types where choosen randomly. A combination of these two types among the randomly choosen tasks where failed based on the failure size given as an input. For example if a failure size of 3 was given as an input, one task of type mProjectPP and two mBackground where selected and their corresponding resources where terminated to orchestrate failure events.

6.7 Results

In this section, the results to illustrate the key contributions of this chapter are provided. The resource provisioner instantiated a pool of spot instances initially on the public AWS cloud and on-demand instances where created when needed on private cloud. The fault-tolerance and on-demand provisioning of our system are discussed in this section.

Figure 6.8 illustrates the effect of failures on the workflow makespan. We can observe that as the failures increase, the makespan increases. Since a retry fault-tolerant technique is used, failures increase the makespan. This experiment demonstrates that the workflow management system can mitigate resource or other failures and can successfully retry the task on another resource ensuring successful execution. After a resource fails, the algorithm remaps all tasks that where scheduled on the failed resource, thus saving execution time.

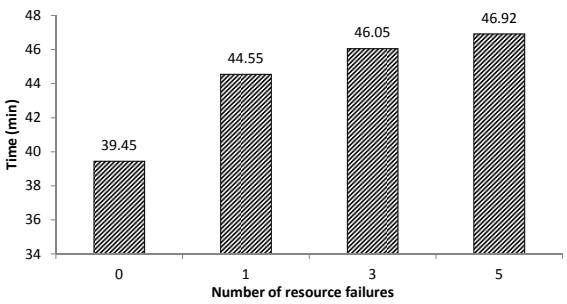

Figure 6.8: Effect on makespan under failures.

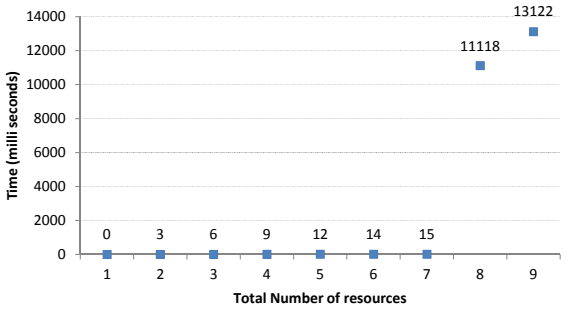

Figure 6.9: Resource instantiation time.

Figure 6.9 shows the resource instantiation times. It can be noticed that a bulk of resources where created initially within the first 15 milliseconds, as stated in the algorithm and few resources where created at the later part of the execution when required by the scheduler in an on-demand fashion. This demonstrates the capability of the algorithm to create cloud resources on-demand in a dynamic manner.

The workflow makespan is higher as it schedules the resources on two cloud infrastructures. The data transfer time, the data movement time between tasks, and the reporting time to the broker and the storage host increases in such an environment, affecting the overall makespan. Running a workflow in a single cloud infrastructure produces far lower makespan. To validate this, we ran the entire workflow on the private cloud and could achieve makespan of 7.84 minutes i.e., 80.13% lower makespan than running on two cloud infrastructures subject to latency and network delays. Running on two cloud infrastructures is essential when there is a private cloud and its resources are limited but the cost of running is free. So a public cloud could be used for the additional workloads reducing. Such a system would increase the time but will reduce the cost significantly than running the entire application on a public cloud.

Nonetheless, we have successfully demonstrated that the Cloudbus workflow management system can provision resources on a multi-cloud environment seamlessly in robust manner. Figure 6.10 is the output mosaic of the montage workflow.

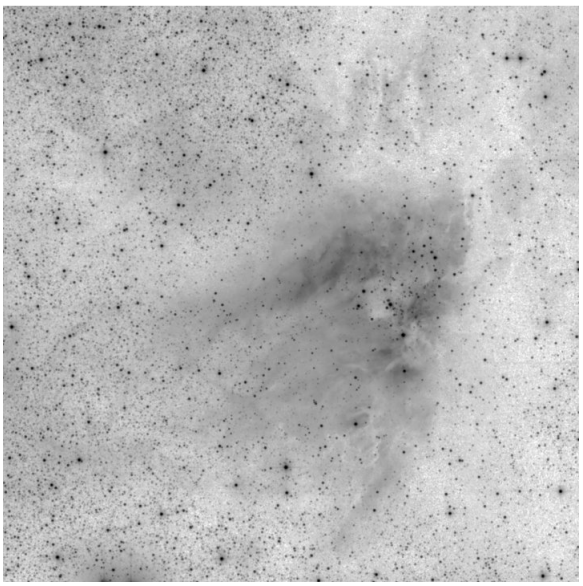

Figure 6.10: Output mosaic of the montage workflow.

6.8 Related Work

Workflow management system presented in this chapter is a flexible, loosely-coupled system that allows multiple plug-ins and it provides an extensive scope for extension. It uses a host of middleware services such as, file and data movement, provenance, replica management, and various middleware dispatchers provided by the gridbus broker [150]

There are quite a few workflow management systems that are cloud-oriented. Askalon [53] is system built with a service oriented architecture, and uses a single access user portal for workflow submission. It has API support for leasing Amazon EC2 instances for its execution. Similarly Pegasus [3,42] provides a workflow engine that supports portability and reuse of components. Pegasus emphasizes performance, reliability, and scalability. It supports desktops, clusters, grids and clouds computing environments. Triana [133] is a modular java workflow environment developed at the Cardiff University. It provides comprehensive library toolbox and allows deployment in grids and clouds. Kepler [8, 92, 101] is another independently extensible, reliable, and open comprehensive system that supports multi-disciplinary applications on grids and clouds. The SwinDeW-C [91] project developed at the Swinburne University, Melbourne is a cloud based peer-to-peer system that is fully accessible through a web based portal.

In comparison to the above listed projects, our workflow management system renders a decentralized scheduling architecture and also allows a loosely-coupled architecture that fosters modularity and aids extensibility. Additionally, this workflow management system has introduced a multi-cloud feature that will facilitate the execution of workflow tasks on multiple cloud infrastructures.

6.9 Summary

In this chapter, the Cloudbus workflow management system a project of CLOUDS Lab at the University of Melbourne has been extended to support dynamic provisioning of cloud resources, supporting multiple cloud providers. This extension to support multiple cloud providers is achieved through the integration of opensource Apache jclouds toolkit. We have also presented a resource provisioning algorithm for a multi-cloud environment. Additionally, we have implemented a retry fault-tolerant mechanism to mitigate failures at task, resource or network levels. Faults at various task stages, such as ready, submitted, stage-in, stage-out can be handled seamlessly and this is demonstrated through our experiments using an astronomy application case study.

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Chapter 7
Conclusions and Future Directions

This chapter summarizes the research work on robust and fault-tolerant workflow scheduling on cloud computing platforms presented in this thesis and highlights the major findings. It also outlines the future directions and open research challenges in this area.

7.1 Summary of Contributions

CLOUD computing offers low-cost computing services as a subscription based service, which are elastically scalable, and dynamically provisioned. Additionally, it also provides attractive pricing models like on-demand and spot instances. Because of which, scientific workflow management systems are rapidly moving towards it. However, cloud environments are prone to failures and performance variations among resources.

In this regard, this thesis set out with one core objective to develop *fault-tolerant scheduling algorithms for workflows*. To accomplish this, we proposed and investigated various fault-tolerant techniques, pricing models, scheduling heuristics, and resource selection policies. Further, in this section we detail each of these findings.

Fault-tolerance is crucial for such large scale complex applications running on failure-prone distributed environments. Given the large body of research in this area, in chapter 2, we provided a comprehensive view on fault-tolerance for workflows in various distributed environments.

In particular, this chapter provided a detailed understanding of faults from a generic viewpoint (e.g. transient, intermittent, and permanent) and a processor viewpoint (such

as, crash, fail-stop and byzantine). It also described techniques such as replication resubmission, checkpointing, provenance, rescue-workflow, exception handling, alternate task, failure masking, slack time, and trust-based approaches used to resolve these faults by which, a transparent and seamless experience to workflow users can be offered.

Apart from the fault-tolerant techniques, we provided an insight into numerous failure models and metrics. Metrics range from makespan oriented, probabilistic based, reliability based, and trust-based among others. These metrics inform us about the quality of the schedule and quantify fault-tolerance of a schedule.

Prominent WFMSs are detailed and positioned with respect to their features, characteristics, and uniqueness. Lastly, tools such as those for describing workflow languages, data-management, security and fault-tolerance, tools that aid in cloud development, and support systems (including social networking environments, and workflow generators), were introduced.

Chapter 3 presented three resource allocation policies with robustness, makespan, and cost as its objectives. This is one of the early works in robust and fault-tolerant workflow scheduling on Clouds, considering deadline and budget constraints. The resource allocation policies judiciously add slack time to make the schedule robust considering the deadline and budget constraints. We test our policies with two failure models for five scientific workflows with two metrics for robustness. Results indicated that our policies are robust against uncertainties like task failures and performance variations of VMs.

Among the proposed policies presented, one of the policies showed the highest robustness and at the same time minimized makespan of the workflow. This policy provided a robust schedule with costs marginally higher than the reference algorithms considered. The weights of the weighted policy presented in this chapter can be varied according to the user priorities. Overall, our policies provided robust schedules with a the lowest possible makespan. They also show that with increase in budget, our policies increase the robustness of the schedule with reasonable increase in cost.

In Chapter 4, two scheduling heuristics that map workflow tasks onto spot and on-demand instance were presented. They minimize the execution cost by intelligently utilizing the variety of pricing models offered by the cloud providers. They are shown to

be robust and fault-tolerant towards out-of-bid failures and performance variations of cloud instances. A bidding strategy that bids in accordance to the workflow requirements to minimize the cost was also presented. This work also demonstrated the use of checkpointing and offers cost savings up to 14%. Simulation results showed that cost reductions of upto 70% were achieved under relaxed deadlines, when spot instances were used.

In Chapter 5, we have proposed two just-in-time adaptive workflow scheduling heuristics for clouds that use task retry and task replication fault-tolerant techniques. These heuristics use on-demand and spot instances to provide fault-tolerant schedules whilst minimizing time and cost. They are fault-tolerant against performance variations, out-of-bid failures, and resource failures. Extensive simulations have shown that the proposed heuristics generate schedules with significantly lower failure probabilities. The makespan of these schedules are also much lower than the baseline algorithm. These heuristics are also shown to maximize resource utilization. These experiments establish that pricing models offered by cloud providers can be used to reduce costs and makespan and at the same time offer robust and resilient schedules.

Finally, in Chapter 6 we have developed a multi-cloud framework for the cloudbus workflow management system. Workflow applications can use this resource plug-in to schedule resources in a multi-cloud environment. We demonstrated this capability through an astronomy workflow application case study using a openstack private cloud and an Amazon AWS public cloud. In this chapter we also developed a novel heuristic for multi-cloud environment.

7.2 Future Research Directions

The research pertaining to thesis is expected to continuously evolve along with the developments in the cloud computing field. Therefore, the challenges and issues also evolve and need fresh contributions. In spite of the significant contributions of this thesis in developing fault-tolerant scheduling algorithms for cloud computing platforms, there are several open research challenges that need to be addressed. This section delineates open

research areas and future directions in this regard.

7.2.1 Cloud Failure Characteristics

Although fault types are known in the current works, the frequency of each type of failure, especially in a cloud environment, is not publicly available. There are few traces of public cloud failures; however, the information that can be obtained from them is minimal. Understanding failures and their frequencies in cloud environments can enhance the research of robust workflow management. Failure rates and types vary among private clouds, public clouds, multi-cloud, hybrid clouds, and commodity clouds. Similarly, understanding performance variations of resources among various types of clouds is an open area of research with a great importance to develop robust and reliable WFMSs tailored for each of these environments.

7.2.2 Metrics for Fault-Tolerance

Quantifying fault-tolerance is another challenge as there are multiple metrics with no proper consensus among them. Metrics have been developed for specific problems for various computing environments with multiple assumptions. Developing a generic metric applicable for multiple mechanisms and environments can help to compare different fault-tolerant mechanisms and rank them based on their performance. Proposing such a widely acceptable metric would be a significant contribution in this domain. In this thesis, prominent metrics have been documented that can be helpful in this research.

7.2.3 Cloud Pricing Models

Pricing is an important aspect for a cloud environment. Research that consider a combination of pricing models and their SLAs to provide fault-tolerant mechanisms that are cost-effective are still in their infancy. Additionally, analyzing the impact of the fault-tolerant mechanisms on the incurred cost is also essential. For example, replication uses more resources and adds more cost to the schedule; on the other hand, resubmission increases the execution time with slight increase in cost. It is important to understand the

cost implications of a particular fault-tolerant mechanism.

Recently, spot instance characteristics have also changed. Amazon allows a two minute notice before terminating the instances. This allows for better fault-tolerant behavior. Our proposed algorithms can be extended to addresses this development and this can provided further fault-tolerance in a schedule.

Different cloud providers price instances with different time units. Some price instances per hour, some per minute with or without a flag fall. These pricing behaviors impact different workflows in multiple ways. Choosing the right pricing model for specific workflows is an exciting research question. Added to this, investigation into fault-tolerance in such environments is challenging and needs to be addressed.

7.2.4 Multiple Tasks on a Single Instance

Traditionally, workflows schedule one task on one instance at a given time. However, cloud resources are multi-core processors and some workflow tasks are not moldable i.e., they are not multi-threaded and cannot use all the processors. Therefore, scheduling multiple tasks on a single instance can enable significant cost benefits, although the performance might be impacted. Additionally, it increases the failure probability of those tasks. This is open area where new heuristics can be developed for such a combination of challenges.

7.2.5 Workflow Specific Scheduling

WFMSs can typically run a single workflow, multiple workflows, or a workflow ensemble, i.e., it might vary from a single workflow to a collection of workflows of similar or different types. Challenges in each context are unique and the allocation mechanism must consider this perspective. Associating this aspect with fault-tolerance will make WFMSs more resilient.

A deep understanding of the workflow helps in developing efficient algorithms. Data-intensive workflows require different allocation and fault-tolerant mechanisms than a compute-intensive workflow. WFMS or the user should be able to identify the

workflow types and address their constraints. Intelligent systems need to be built that can capture this information and devise schedule in lieu with them.

7.2.6 Multi-Cloud Challenges

Workflow scheduling, specially for e-science application, involves collaborations spread across geographic regions. Using a multi-cloud environment could address the latency issues involved. However, the prices of resources change from region to region. The failure rates of resources are different. The data transfer cost would need to considered. Models need to be developed to schedule on such a system with multiple heterogeneity. The study of cost and time implications would be a significant contribution in this area.

7.2.7 Energy-Efficient Scheduling

Cloud infrastructures consume vast amount of energy leaving large carbon footprints. Added to this, increase in electricity prices stress the need for energy efficient data centers. Therefore cloud providers and applications using cloud infrastructures must develop energy efficient solutions.

Workflow scheduling algorithms extensively use large number of cloud resources. Hence, a focus on energy-efficient workflow scheduling is much required in addition to existing performance parameters.

7.3 Final Remarks

Cloud computing offers virtualized servers, which are dynamically managed, monitored, maintained, and governed by market principles. As a subscription based computing service, it provides a convenient platform for *scientific workflows* due to features like application scalability, heterogeneous resources, dynamic resource provisioning, and pay-as-you-go cost model. Fault-tolerant scheduling heuristics developed in this thesis enable workflow managements system to schedule complex large scale workflow applications on cloud computing platforms in a robust and fault-tolerant manner whilst minimizing

time and cost. Research such as this, is essential due to the performance variations experienced among cloud resources and various kinds of failure found in the application, environment and the network. The contributions of this thesis helps in making the execution of workflow seamless on cloud computing platforms.

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