

Multiple Workflows Scheduling in Multi-tenant Distributed Systems: A Taxonomy and Future Directions

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Scientific workflows are commonly used to automate scientific experiments. The automation ensures the applications being executed in the order. This feature attracts more scientists to build the workflow. However, the computational requirements are enormous. To cater the broader needs, the multi-tenant platforms for scientific workflows in distributed systems environment were built. In this paper, we identify the problems and challenges in the multiple workflows scheduling that adhere to the multi-tenant platforms in distributed systems environment. We present a detailed taxonomy from the existing solutions on scheduling and resource provisioning aspects followed by the survey in this area. We open up the problems and challenges to shove up the research on multiple workflows scheduling in multi-tenant distributed systems.

CCS Concepts: •Information systems → Computing platforms; •Networks → Cloud computing; •Applied computing → Service-oriented architectures; •Computer systems organization → Cloud computing; Grid computing;

Additional Key Words and Phrases: Scientific Workflows, Multi-tenant Platforms, Multiple Workflows Scheduling

ACM Reference format:

Muhammad H. Hilman, Maria A. Rodriguez, and Rajkumar Buyya. 2016. Multiple Workflows Scheduling in Multi-tenant Distributed Systems: A Taxonomy and Future Directions. 1, 1, Article 1 (January 2016), 33 pages.
 DOI: 10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

Scientific workflows are widely used to automate scientific experiments in many scientific areas. The latest detection of gravitational waves by the LIGO project (Svtil 2016) is an example of scientific breakthrough assisted by workflow technologies. These workflows are composed of multiple tasks and dependencies that represent the flow of data between them. Scientific workflows are usually large-scale applications that require extensive computational resources to process. As a result, distributed systems with an abundance of storage, network, and computing capacity are widely used to deploy these resource-intensive applications.

The complexity of scientific workflows execution urges scientists to rely on workflow management systems (WMS), which manage the deployment of workflows in distributed resources. Their main functionalities include but are not limited to scheduling the workflows, provisioning the resources, managing the dependencies of the tasks, and staging the input/output data. Taverna (Oinn et al. 2004), Kepler (Ludäscher et al. 2006) and Pegasus (Deelman et al. 2015) are some examples of WMS that are widely used by the scientific community. A key responsibility of WMS and the focus of this work is the scheduling of workflow tasks. In general, this process consists of two stages, i) mapping the execution of tasks on distributed resources and ii) acquiring and

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DOI: 10.1145/nnnnnnn.nnnnnnn

allocating the appropriate compute resources to support them. Both of these processes need to be carried out while considering the Quality-of-Service (QoS) requirements specified by users and preserving the dependencies between tasks. These requirements make the workflow scheduling process a challenging problem.

Workflow scheduling was studied and surveyed extensively during the cluster, and grid computing era (Yu and Buyya 2005). Subsequently, when the cloud computing technology emerged as a new paradigm with market-oriented focus, scientific workflows got a promising deployment platform offering multiple benefits to scientists. However, it also brought forth additional challenges. Solutions for cloud workflow scheduling have been extensively researched, and a variety of algorithms have been developed (Wu et al. 2015). Furthermore, various existing taxonomies of workflow scheduling in clouds focus on describing the particular scheduling problem as well as its unique challenges and ways of dealing with them (Smachat and Viriyapant 2015) (Rodriguez and Buyya 2017).

Contrary to these previous studies which focus on a single workflow scheduling, this work addresses the scheduling problem from a higher level view; it considers the scheduling of multiple workflows that arrive continuously. The advent of multi-tenant platforms like clouds and the shifting trend from the traditional on-premises to the utility computing era that is represented by the term "as a service" has led to the emergence of Workflow-as-a-Service (WaaS) platforms. These platforms continuously receive a number of requests for workflow executions from different users and their specified defined QoS requirements. The WaaS provider must then be able to schedule these workflows in a way that each of their requirements is fulfilled. A simple way to achieve this is by allocating a set of dedicated resources to execute each workflow. However, the inter-dependent tasks produce unavoidable idle gaps in the schedule. Hence, dedicating a set of resources for each user can be considered inefficient in environments where multiple workflows are involved as it leads to resources being underutilized. This, in turn, may cause a significant loss for WaaS providers that generate revenue from the utilization of resources. Consequently, the strategies implemented in such platforms should aim to improve the resource utilization while still complying with the unique requirements of different users.

Accommodating multi-tenants with different QoS creates a high complexity management system. The very first problem lies on how such a system handles the different scientific workflows applications. A variety of applications involve different software libraries, dependencies, and hardware requirements. The users should be able to customize the specific configurations along with their defined QoS when submitting the workflows. Furthermore, WaaS systems must have a general scheduling approach to handle different types of computational requirements from different workflows. Another consideration related to multi-tenancy is the strategy to maintain fairness between multiple users that should be achieved through well-defined prioritization in the scheduling and the automatic scaling of the resources. The last aspect that should be noticed in multi-tenant platforms is the performance variability in computational resources as virtualization-based infrastructures like clouds may encounter performance degradation due to the multi-tenancy, virtualization overhead, geographical location, and temporal aspects (Leitner and Cito 2016).

The contribution of this work is the study of the multiple workflows scheduling problem in multi-tenant distributed systems and a survey of existing solutions. The structure of the rest of this paper is as follows. Section 2 discusses the workflow scheduling problem in WaaS platforms while Section 3 addresses its challenges. The proposed taxonomy is presented in Section 4, and the review of existing solutions is covered in Section 5 along with their classification into the taxonomy. Section 6 presents the future directions, and Section 7 summarizes the paper.

2 WORKFLOW SCHEDULING IN WAAS PLATFORMS

Workflow-as-a-Service (WaaS) is an emerging paradigm that offers the execution of scientific workflows as a service. The service provider lies either in the Platform-as-a-Service (PaaS) or Software-as-a-Service (SaaS) layer based on the cloud stack service model. WaaS providers make use of distributed computational resources to serve

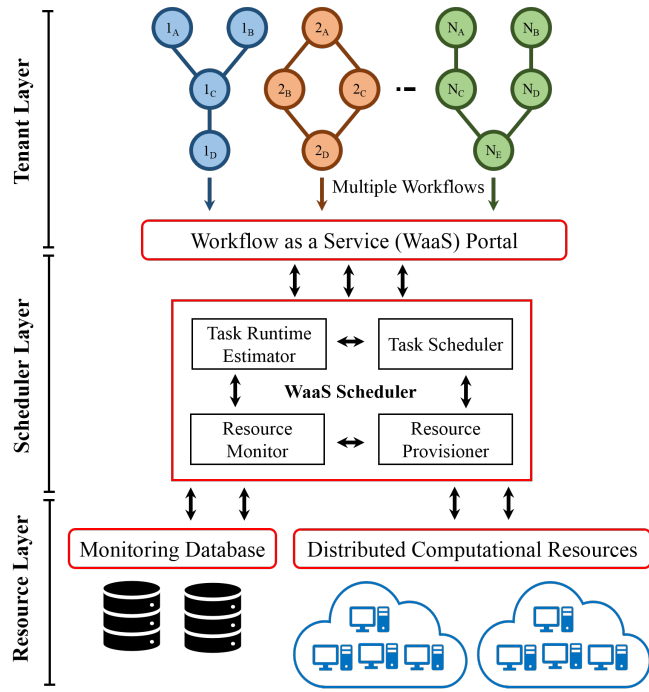


Fig. 1. Workflow as a Service Architecture

the enormous need of computing power in the execution of scientific workflows. They provide a holistic service to scientists starting from the user interface in the submission portal, applications installation and configuration, staging of input/output data, workflow scheduling, and resource provisioning. WaaS platforms are designed to process multiple workflows from different users. The workload is expected to arrive continuously, and workflows must be handled as soon as they arrive due to the quality of service (QoS) constraints defined by the users. Therefore, WaaS platforms must deal with a high level of complexity derived from their multi-tenant and dynamic nature, contrary to a traditional WMS that is commonly used for managing a single workflow execution.

Several variations of WaaS framework- which extend the traditional WMS architecture- are found in literature such as the work by Wang et al. (Wang et al. 2014) describing a service-oriented architecture for scientific workflows that separates the components into user management layer, scheduler, storage, and VM management. Meanwhile, a framework with a similar division that emphasizes on distributed storage is proposed by Esteves and Veiga (Esteves and Veiga 2016). Another typical architecture for multi-tenant scientific workflows execution in clouds embraces the proposed framework as a service layer above the Infrastructure as a Service (IaaS) layers (Rimal and Maier 2017). In general, we identified three primary layers in WaaS platforms; the tenant layer, the scheduler layer, and the resource layer. Based on three layers and the identified requirements of WaaS platforms, we propose a reference architecture for this system focusing on the scheduler component as depicted in Figure 1.

Firstly, the tenant layer manages the workflows submission where users can configure their preferences and define the QoS of their workflows. The scheduler layer is responsible for placing the tasks on either existing or newly acquired resources and consists of four components: task runtime estimator, task scheduler, resource provisioner, and resource monitor. The task runtime estimator is used to predict the amount of time a task will take to complete in a specific computational resource (i.e., virtual machine). The task scheduler is used to map a

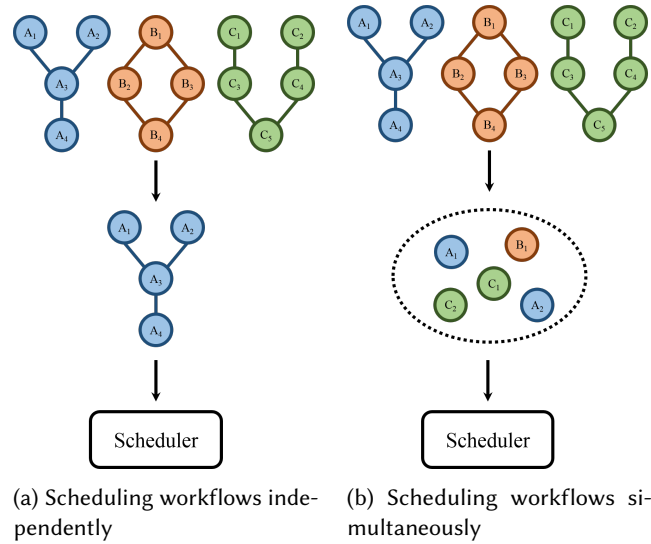


Fig. 2. Scheduling Multiple Workflows

task into a selected virtual machine for execution. The resource provisioner is used to acquire and release virtual machines from third-party providers. The resource monitor is used to collect the resource consumption data of a task executed in a particular virtual machine. These data are stored in a monitoring database and are used by the task runtime estimator to build a model to estimate the task's runtime. The third-party infrastructure (e.g., virtual machines, storage databases) with which the WaaS platforms interact, fall into the resource layer.

The scope of this work is limited to algorithms scheduling workflows that are modeled into directed acyclic graphs (DAGs) where a workflow W consists of a set of tasks $T = (t_1, t_2, \dots, t_n)$ and a set of directed edges $E = (e_{12}, e_{13}, \dots, e_{mn})$ in which an edge e_{ij} represents a data dependency between task t_i (parent task) and task t_j (child task). Hence, t_j will only be ready for execution after t_i has completed. In this way, the purpose of DAG scheduling is to allocate the tasks to computational resources in such fashion that the precedence constraints among the tasks are preserved. Within this context, the workflow scheduling problem is defined by the application model of WaaS platforms. Specifically, the workflows submitted to WaaS platforms belong to different users and are not necessarily related to each other. As a result, heterogeneity becomes a defining characteristic of the workload that covers various aspects of workflows including the type of applications, the size of the workflows, and the user-defined QoS.

Furthermore, even though the information of workflows (i.e., topological structure, computational requirement, size, input) are available when these workflows arrive into WaaS platforms, planning the schedule by exploiting this information as being implemented in static workflow scheduling is not plausible. For example, a strategy of partitioning tasks before runtime in a static workflow scheduling to minimize the data transfer is proven to be efficient for data-intensive workflows (Ahmad et al. 2014). This actually can be done in WaaS platforms, but then, it becomes an inevitable bottleneck since the time required for partitioning a workflow may delay next queue of arriving workflows for scheduling. The waiting time may increase significantly if the planning involves a metaheuristic optimization technique that known for its intensiveness in computing. As the size of the workflow increases, this pre-processing time may become longer and produce more massive queue with significant waiting time delay. Hence, we do not consider solutions that schedule each workflow independently as depicted in Figure 2a as this approach is no different to scheduling a single workflow.

Instead, we consider scheduling algorithms designed to schedule multiple workflows simultaneously as shown in Figure 2b. There are many advantages and challenges of scheduling multiple workflows in this area. The main advantages of this scheduling model are related to the possibility of idle time slots produced by a particular workflow to be used by another workflow and the reduction of waiting time from queueing delay of workflows being scheduled. On the other hand, the challenges to achieving these are not trivial. Handling the workloads heterogeneity, managing the continuous arriving workflows, implementing general scheduling approaches that deal with different requirements, and dealing with performance variability in distributed systems are questions that must be answered. These challenges are discussed in detail in Section 3.

3 CHALLENGES

In this section, we discuss various challenges of scheduling multiple workflows in multi-tenant distributed systems. These are derived from the *workload heterogeneity*, the *quality of service diversity*, the *fairness and priority*, and the *performance variability* aspects.

3.1 Workload Heterogeneity

Workload heterogeneity can be described from several aspects including the continuous arrival of workflows at different times, the various types of workflow applications that differ in computational requirements, the difference in workflow sizes, and the diversity in software libraries and dependencies.

The different arrival time of multiple workflows in WaaS platforms resembles the problem of streaming data processing that deals with continuous incoming tasks to be processed. In contrast with some static workflow scheduling algorithms that make use of the workflow structure, the runtime of tasks, and the specific computational requirements before execution time to create a near optimal schedule plan, the continuous arrival of workflows in WaaS platforms makes this an unsuitable approach. Furthermore, conventional techniques to achieve near-optimal schedule such as metaheuristics are computationally intensive, and the computational complexity will grow as the workflow size increases. In fact, the time for planning may take longer than the actual workflow execution. Hence, a lightweight dynamic scheduling approach is the most suitable for WaaS environments as the algorithms must be able to deal with the dynamicity of the workload. For instance, at peak time the concurrency of requests may be very high, whereas, at other times, the submission rate may reduce to a point where the inter-arrival time between workflows is long enough to execute each workflow in a dedicated set of resources.

The variety of application types is another issue to be addressed. A study by Juve et al. (Juve et al. 2013) shows a variety of workflow applications with different characteristics. The Montage astronomy workflow (Deelman et al. 2008) that is used to reconstruct mosaics of the sky is considered as a data-intensive application with high I/O activities. The CyberShake workflow (Maechling et al. 2007) that is used to characterize earthquake hazards using the Probabilistic Seismic Hazard Analysis (PSHA) techniques is categorized as a compute-intensive workflow with multiple reads on the same input data. The Broadband workflow that is used to integrate a collection of simulation codes and calculations for earthquake engineers has a relative balance of CPU and I/O activities in its tasks. These three samples show different types of workflow applications that may have different strategies of scheduling to be carried out. For example, a strategy of clustering tasks with a high dependency of input/output data (i.e., data-intensive) and allocating the same resource for them to minimize data transfer.

Furthermore, the heterogeneity of workloads is also related to the size of the workflows. The size represents the number of tasks in a workflow and may differ even between instances of the same type of workflow application due to different input datasets. For example, the Montage workflow (Deelman et al. 2008) takes the parameters of width and height degree of a mosaic of the sky as input. The higher the degree, the larger the size of Montage workflow to be executed as it resembles the size and shape of the area of the sky to be covered and the sensitivity of the mosaic to produce. A large-scale workflow may raise another issue in scheduling such as high volume

data transfer that may cause a bottleneck in the network which will affect other smaller scale workflows being executed in the platform.

Another heterogeneity issue in WaaS platforms is the various software libraries and dependencies required for different workflows. This problem is related to the deployment and configuration of workflows in WaaS platforms. Deploying different software libraries and dependencies in a system requires technical efforts such as installing the software and managing conflicts between software dependencies. The most important implication related to this case is the resource sharing between workflows to utilize idle time slots produced during the scheduling. In cluster and grid environments where every user uses shared installed software systems on a physical machine, the conflicting dependencies are inevitable. This problem can be avoided by isolating applications in virtualized environments such as clouds. However, in clouds where the workflow's deployment and configuration can be isolated in a virtual machine, the possibility to share the computational power between users in a particular virtual machine is limited. This is due to the limitation of a virtual machine capacity (i.e., memory, storage) and possible conflicting dependencies if we want to have as much as software configured in a virtual machine instance. The trade-off between the isolation and the resource sharing in clouds can be solved using container technology. In this case, container, a lightweight operating system level virtualization, is used to isolate the workflow application before deploying them on virtual machines. Therefore, both isolation and resource sharing objectives can be achieved.

3.2 Quality of Service Diversity

All of the workflow scheduling algorithms have the same purpose of finding the most optimal configuration of task-resource mapping. However, each user may have different requirements regarding the quality of service (QoS). In general, there are two common QoS requirements in workflow scheduling, namely time and cost. The majority of the cases require the algorithms to minimize the overall execution time of the workflow (i.e., makespan). On the other hand, the cost of executing the workflows significantly affects the scheduling decisions in utility-based computational infrastructures such as utility grids and cloud environments. It is evident that every user wants to minimize the cost of executing their workflows. These two objectives have opposing goals and a trade-off between them must be considered. This trade-off then is derived into various scheduling objectives such as minimizing cost while meeting the deadline (i.e., the time limit for execution), minimizing makespan while meeting the budget (i.e., the cost limit for execution), and a more loose objective, meeting deadline, and budget.

In WaaS platforms, the *QoS diversity* is prevalent due to the different needs of users to execute their workflows. The diversity is not only related to the QoS values the users define but also may raise in the form of different scheduling objectives. The various user-defined QoS requirements must be handled in a way that each user's need can be fulfilled without sacrificing the other users served by the systems. This issue implies the challenge of maintaining fairness between users in WaaS platforms.

3.3 Fairness and Priority

Fairness and priority issues are inevitable in multiple workflows scheduling. Given two workflows that arrive at the same time, the decision to execute a particular workflow first must be determined based on some policy. The priority to be assigned for each workflow can be derived from several aspects including the QoS defined by users, the type of workflow application, the user's priority, and the size of the workflows.

Priority assignment can be determined based on the user-defined QoS. It is evident for scheduling algorithms to prioritize a workflow with the earliest deadline as this can ensure the fulfillment of QoS requirements. In this way, algorithms may introduce a policy based on the deadline that delays the scheduling of a workflow with a more relaxed deadline to improve the resource sharing in the system without violating the fairness aspect. On the other hand, the priority assignment can be defined from the budget available. In real-world practice, it is common

to prioritize the users with more budget available to do a particular job compared to the lower one (e.g., priority check-in for business class passenger). This policy also can be implemented in multiple workflows scheduling.

Assigning priority based on the type of application can be done by defining application or user classes. For example, workflows submitted for education or tutorial purpose may have a lower priority than the workflows executed in a scientific research project. Meanwhile, a workflow that is used to predict the typhoon occurrence may be executed first compared to a workflow for creating the mosaic of the sky. This policy can be defined out of the scheduling process based on some policy adopted by WaaS providers.

Moreover, the priority assignment can also be determined based on the size of workflows. This is the most traditional way of priority scheduling that has been widely implemented such as the Shortest Job First (SJF) policy which prioritizes the smaller workflows over a larger one to avoid starvation. Another traditional scheduling algorithm like the Round-Robin (RR) also can be constructed based on the size of the workflows to ensure both of the small and large-scale workflows get a fair treatment in the systems.

3.4 Performance Variability

Handling the *performance variability* in multi-tenant distributed systems is essential to the multiple workflows scheduling problems as the scheduling highly relies on the accurate estimation of workflow's performance on a particular computational infrastructure. Attempts to increase the quality of scheduling by accurately estimating the time needed for completing a task, as one of the strategies for taking care of the uncertainty, has been studied. For example, a work by Real et al. (Real et al. 2003) presented an attempt to handle the uncertainty of infrastructure performances in grid workflow scheduling using a Bayesian network to estimate the future resource utilization based on current CPU availability. Meanwhile, Pham et al. (Pham et al. 2017) worked on machine learning techniques to predict task runtime in workflows using a two-stage prediction approach.

When we specifically discuss cloud environments, the uncertainty becomes higher than cluster and grid environments. The virtualization that is the backbone of clouds is the primary source of the *performance variability* as reported by Leitner and Cito (Leitner and Cito 2016) and also previously discussed by Jackson et al. (Jackson et al. 2010). The cloud instances performance varies over time due to several aspects including the virtualization overhead, the geographical location of the data center, and especially the multi-tenancy of clouds. For example, it is not uncommon for a task to have a longer execution time during a specific time in cloud instances (i.e., peak hours) due to the number of users served by a particular cloud provider at that time. The main conclusions from their works substantiate our assumption that the performance and predictability of cloud environments is something that is not easy to address.

Another variable of uncertainty in clouds is the provisioning and deprovisioning delays of VMs. When the user requests to launch an instance in a cloud, there is a delay between the request and when the VM is ready to use, called provisioning delay. There also exists a delay in releasing the resource, namely deprovisioning delay. Not considering the provisioning and deprovisioning delays in the scheduling phase may cause a miscalculation of when to acquire and to release the VM. This error may cause an overcharging bill of the cloud services. A study by Mao and Humphrey (Mao and Humphrey 2012) reported that the average provisioning delay of a VM, observed from three cloud providers—Amazon EC2, Windows Azure, and Rackspace—was 97 seconds while more recently, Jones et al. (Jones et al. 2016) presented a study which shows that three different cloud management frameworks—OpenStack, OpenNebula, and Eucalyptus—produced VM provisioning delays between 12 to 120 seconds. However, delays are not only derived from acquiring and releasing instances. As most of the WMS treat cloud instances (i.e., virtual machines) as virtual clusters using third-party tools (e.g., HTCondor¹), there exists a delay in integrating a provisioned VM from cloud providers into a virtual cluster. An upper bound delay of 60 seconds for this process was observed by Murphy et al. (Murphy et al. 2009) for an HTCondor virtual cluster.

¹<https://research.cs.wisc.edu/htcondor/>

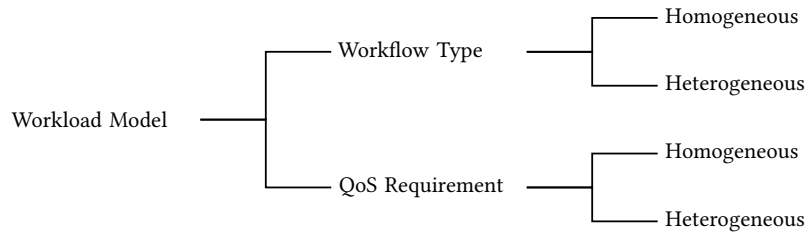


Fig. 3. Workload Model Taxonomy

These delays are one of the sources of uncertainty in clouds, and therefore, the algorithms should consider them to get an accurate scheduling result.

4 TAXONOMY

The scope of this study is limited to the algorithms developed for multiple workflows scheduling in multi-tenant distributed systems that represent the problem in WaaS platforms. In this section, we describe each taxonomy classification, while the mapping and references of the algorithms to each class are presented in Section 5.

4.1 Workload Model Taxonomy

Multiple workflows scheduling algorithms are designed to handle specific workloads that represent a multi-tenant problem in WaaS platforms. These workloads can be differentiated by their workflow type and user-defined QoS requirements as shown in Figure 3.

4.1.1 Workflow Type. Scheduling algorithms for WaaS platforms must consider the fact that the users in this multi-tenant system may submit different or a single type of workflow applications. These variations can be categorized into *homogeneous* and *heterogeneous* workflow types.

A *homogeneous* workflow type assumes all users submit the same type of workflow applications (e.g., WaaS platforms for Montage astronomical workflow). In this case, the algorithms can be tailored to handle a specific workflow application by exploiting its characteristics (e.g., topological structure, computational requirements, software dependencies, and libraries). For example, related to a topological structure, a workflow with a large number of tasks in a level may raise an issue of data transfer. This can potentially become a communication bottleneck when all of the tasks in a level concurrently transfer the data input needed to execute the tasks. Therefore, clustering the tasks may result in a reduction in data transfer and eliminates the bottleneck in the system. Furthermore, the heterogeneity from the resource management perspective affects how the scheduling algorithms handle software dependencies and libraries installed in computational resources. The algorithms for a *homogeneous* workflow type can safely assume that all resources contain the same software for a typical workflow application. In this way, the constraints for choosing appropriate resources for particular tasks related to the software dependencies can be eliminated, since all of the resources are installed and configured for the same workflow application.

On the other hand, to handle a *heterogeneous* workflow type, the algorithms must be able to tackle all various possibilities of workflow type submitted into WaaS platforms. In a WaaS platform, where the *heterogeneous* workflow type is considered, tailoring the algorithms to the specific workflow application characteristics is impractical. The scheduling algorithms must be designed following a more generic approach. For example, related to a topological structure, a task in a workflow is considered ready for an execution when all of its predecessors

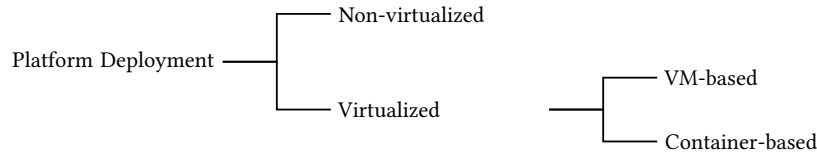


Fig. 4. Deployment Model Taxonomy

are executed, and its data input is available in a resource allocated for execution. In this way, the algorithms can exploit a simple heuristic to build a scheduling queue by throwing in all tasks with this specification to the queue.

Furthermore, a variety of software dependencies and libraries required for different workflow applications increases the possible conflict of software dependencies in platforms that consider *heterogeneous* workflow type. Therefore, the algorithms must include some rules in the resource selection step to determine what relevant resources can be allocated for specific tasks. For example, the algorithms can define a rule that is only allowing a task to be allocated a resource based on its software dependencies and libraries availability.

4.1.2 QoS Requirements. Workloads in WaaS platforms must be able to accommodate multiple users' requirements. These requirements are represented by the Quality of Service (QoS) parameters defined when users submit their workflows to the platforms. We categorize the workloads based on the users' QoS requirements into *homogeneous* and *heterogeneous* QoS requirements.

The majority of algorithms designed for WaaS platforms surveyed in this study consider a *homogeneous* QoS requirement. They are designed to achieve the same scheduling objective (e.g., minimizing makespan, meeting the budget) for all workflows. Meanwhile, a *heterogeneous* QoS requirement is addressed by the ability to be aware of various objectives and QoS parameters demanded by a particular user. The algorithms may consider several strategies within the same WaaS platforms to handle workflows with different QoS requirements. For example, to process workflows that are submitted with the deadline constraints, the algorithms may exploit the option to schedule them into the cheapest resources to minimize operational cost as long as their deadlines can be met. At the same time, the algorithms can also handle workflows with the budget constraints by using another option to lease as much as possible the fastest resources within the available budget.

4.2 Deployment Model Taxonomy

The scheduling algorithms for WaaS platforms can be differentiated based on the WaaS deployment model. We identified two types of algorithms for WaaS platforms based on their deployment model as illustrated in Figure 4. Different issues and challenges that arise from these deployment models are worthy to be considered by the scheduling algorithms.

4.2.1 Non-virtualized. The majority of works in our survey design are scheduling algorithms for cluster and grid environments. These two environments are the traditional way of establishing multi-tenant distributed systems where a large number of computational resources are connected through a fast network connection, so it can be utilized by many users in a shared fashion. However, in this way, there is no isolation between software installed related to their dependencies and libraries within the same physical machine.

Accommodating multi-tenant in a non-virtualized environment is limited by the static capacity of computational infrastructure. This makes auto-scaling of resources is difficult to be done in the non-virtualized environments. Thus, the algorithms cannot efficiently serve a dynamic workload without having a queueing mechanism to schedule overloaded requests at a particular time. For example, adding a node into an established cluster infrastructure is possible but may involve technicalities that cannot be addressed in a short period of time. This environment also does not allow the users to shrink and expand their allocated resources easily, since it needs to

go through the administrator intermediaries. Therefore, the primary concern of scheduling algorithms designed for this environment is to ensure for a maximum utilization of available resources, so the algorithms can reduce the queue of users waiting to execute their workflows. In this case, the techniques—such as task rearrangement and backfilling—can be used to fill the gaps produced by scheduling a particular workflow, by allocating these idle slots to other workflows.

4.2.2 Virtualized. The algorithms designed for virtualized environments (i.e., cloud computing environments) can gain advantages from a flexible configuration of VM as it isolates specific software requirements needed by a user in a virtualized instance. A fully configured virtual machine can be used as a template and can be shared between multiple users to run the same workflows. This isolation ensures little disturbance to the platforms and the other users whenever a failure occurs. However, in this way, possible computational sharing of a virtual machine is limited. It is not plausible to configure a virtual machine for several workflow applications at the same time. In this case, containers can be used to increase the configuration flexibility in virtualized environments. The container is an operating-system-level virtualization method to run multiple isolated processes on a host using a single kernel. The container is initially a feature built for Linux (i.e., LXC) that is further developed and branded as a stand-alone technology (e.g., Docker²) that not only it can run on Unix kernel but also on Windows NT kernel (e.g., windows container³). A full workflow configuration can be created in a container before deploying it on top of virtual machines. In this way, the computational capacity of VMs can be shared between users with different workflows.

In the context of scalability, algorithms designed for virtualized environments can easily accommodate multi-tenant requirements. The algorithms can acquire more resources in on-demand fashion whenever requests are overloading the system. Furthermore, this on-demand flexibility supported by pay-as-you-go pricing scheme reduces the burden for WaaS providers to make upfront payments for reserving a large number of resources that may only be needed at a specific time (i.e., peak hours). Even if a particular cloud provider cannot meet the demand of WaaS providers, the algorithms can provision resources from different cloud providers.

However, this environment comes with a virtualization overhead that implies a significant performance variability. The overhead not only occurs from the communication bottleneck when a large number of users deal with high volume data, but also the possible degradation of CPU performance since the computational capacity is shared between several virtual machines in the form of virtual CPU. The other overheads are the delay in provisioning and deprovisioning virtual machines and the delay in initiating and deploying container. The scheduling algorithms have to deal with these delays and consider them in the scheduling to ensure the accurate scheduling result.

4.3 Priority Assignment Model

Fairness between users in multi-tenant platforms can be achieved through priority assignment in scheduling algorithms. This assignment is essential as the ultimate goal of WaaS providers is to fulfil each user's QoS requirement. We identify various priority assignment model from surveyed algorithms that consider the type of workflow application, users QoS constraints, user self-defined priority, and size of workflows in their design, as shown in Figure 5.

4.3.1 Application Type. Different types of workflow application can be used to define the scheduling priority based on their context and critical functionality. The same workflow application can differ in priority when it is used in a different environment. Montage Astronomy workflow used for an educational purpose may have a lower priority than a solar research project using the same workflow. Meanwhile, considering the different

²<https://www.docker.com/>

³<https://docs.microsoft.com/en-us/virtualization/windowscontainers/>

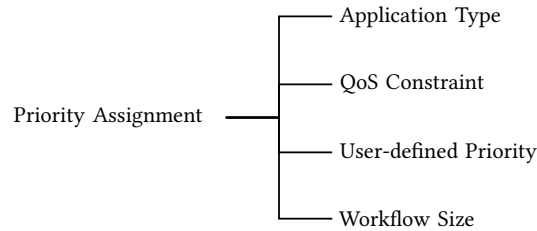


Fig. 5. Priority Assignment Model Taxonomy

critical functions of workflows and some events (e.g., an earthquake event occurs on some sites) some workflow applications can be prioritized from the other. For example, CyberShake workflow to predict the ground motion after an earthquake may be prioritized compared to Montage workflow that is used to create a mosaic of the sky image. This priority assignment needs to be designed in a specific policy of WaaS providers that can regulate the fairness of the scheduling process.

4.3.2 QoS Constraint. Deriving priority assignment from users' QoS constraint can be done within the scheduling algorithms. This assignment is included in the logic of algorithms to achieve the scheduling objectives. For example, an algorithm that aims to minimize cost while meeting the deadline may consider to de-prioritize and delay a task of a particular workflow that has a more relaxed deadline to re-use the cheapest resources available. In this way, the algorithms must be designed to be aware of the QoS constraints of the tasks to derive these parameters into a priority assignment process during the scheduling. Furthermore, the challenge of deriving priority assignment from QoS constraints may come from a *heterogeneous* QoS requirement workload. The algorithms must be able to determine a priority assignment for multiple workflows with different QoS requirements. For example, given two workflows with different QoS parameters, a workflow was submitted with a deadline, while another was included with a budget. The priority assignment can be done by combining these constraints with its application type, user-defined priority or workflow structure.

4.3.3 User-defined Priority. On the contrary to the application type priority model that may be arranged through a specific policy, priority assignment must also consider the user-defined priority in scheduling algorithms. This priority can be defined by users with appropriate compensations for WaaS providers. For example, it is not uncommon in the real-world practice to spend more money to get a prioritized treatment that affects the speed of process and quality of service (e.g., regular and express postal service). It is possible in WaaS platforms to accommodate such mechanism where the users are given the option to negotiate their priority through a monetary cost compensation for WaaS providers. In fact, this is a standard business practice adopted in multi-tenant platforms (e.g., pricing schemes of reserved, on-demand, and spot instances).

4.3.4 Workflow Size. Another approach on priority assignment is based on the structure of workflows (e.g., size, parallel tasks, critical path). Prioritizing workflows based on their sizes resembles a traditional way of priority scheduling, such as Shortest Job First (SJF) policy that gives priority to the shortest tasks, and Round Robin (RR) policy that attempts to balance the fairness between tasks with different sizes. This prioritization can be combined with the QoS constraint to produce better fairness between users. For example, a large-scale workflow may have a very extended deadline. Therefore, smaller workflows with tight deadlines can be scheduled between the execution of tasks from this larger workflow.

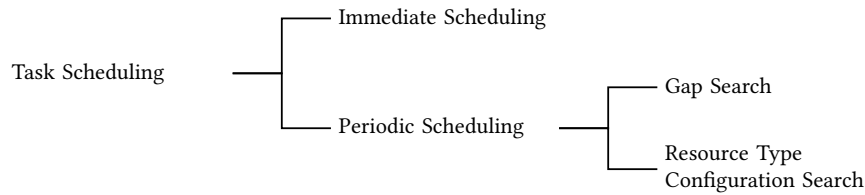


Fig. 6. Task Scheduling Model Taxonomy

4.4 Task Scheduling Model

Task-resource mapping is the primary activity of scheduling. All of the surveyed algorithms avoid the meta-heuristics approach that is known for its intensiveness to plan the schedule before runtime. This planning creates an overhead waiting delay as the continuous arriving workflows have to wait for pre-processing before the actual scheduling takes place. Therefore, they use dynamic approaches which reduce the need for intensive computing at the planning phase and aim to achieve a fast scheduling decision by considering the current status of the systems. These approaches can be divided into *immediate* and *periodic* scheduling as illustrated in Figure 6.

4.4.1 Immediate Scheduling. Immediate scheduling or just-in-time scheduling is a dynamic scheduling approach in which tasks are scheduled whenever they are ready for scheduling. In the case of multiple workflows, this scheduling approach collects all of the ready tasks from different workflows in a task pool before deciding to schedule based on some particular rules. The immediate scheduling tries to overcome the fast dynamic changes in the environments by adapting the decision based on the current status of the system. However, as the algorithm schedules the tasks based on a limited amount of information (i.e., limited view of the previous and future information), this approach cannot achieve an optimal scheduling plan, but it is an efficient way for WaaS platforms that deal with uncertain and dynamic environments.

The immediate scheduling resembles list-based heuristics scheduling. This scheduling approach, in general, has three scheduling phase, task prioritization, task selection, and resource selection. The algorithms repeatedly select a particular task from the scheduling queue that is constructed based on some prioritization method, and then selects the appropriate resource for that particular task. For example, in deadline constraint-based heuristics algorithms that aim to minimize the cost while meeting the deadline, the scheduling queue is constructed based on the earliest first deadline (EDF) of the tasks and the cheapest resources that can meet the deadline are chosen to ensure the cost minimization. The time complexity for heuristic algorithms is low. Therefore, it is suitable for multiple workflows scheduling algorithms that deal with the speed to manage the scheduling process for multi-tenant systems.

4.4.2 Periodic Scheduling. Periodic scheduling approach schedules the tasks periodically to exploit the possibility to optimize the scheduling of a set of tasks within a period. While in a general batch scheduling, a particular set is constructed based on the size of workload (i.e., schedule the tasks after reaching a certain number), and periodic scheduling schedules the tasks in a set of timeframe. In this case, the periodic scheduling acts as a hybrid approach between static and dynamic scheduling methods. Static, in a way that the algorithms exploit the information of a set of tasks (i.e., structures, estimated runtime) to create an optimal plan, but it does not need to wait for a full workload of tasks to be available. The dynamic sense of algorithms adapts and changes the schedule plan periodically. Hence, the periodic scheduling refers to a scheduling technique that utilizes the schedule plan of a set of tasks available in a certain period to produce a better scheduling result. This method is more adaptable to changes and has faster pre-runtime computation than static scheduling techniques, since it only includes a small fraction of workload to be optimized rather than the whole workload before runtime. On

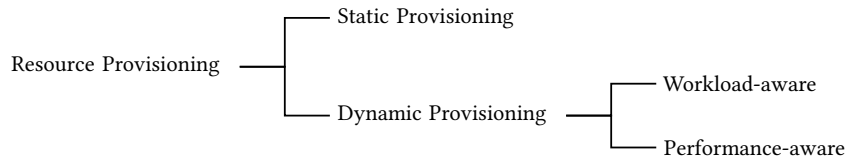


Fig. 7. Resource Provisioning Model Taxonomy

the other hand, this approach can achieve a better result from having an optimized schedule plan than a typical just-in-time (i.e., immediate) scheduling but with less speed—as a trade-off—to schedule the tasks.

One of the approaches in periodic scheduling is identifying the gaps between tasks during the schedule. The identification uses an estimated runtime of tasks and their possible position in a resource during runtime. The most common techniques to fill the gap identified in the scheduling plan are task rearrangement and backfilling strategy. Task arrangement strategy re-arranges the tasks scheduling plan to ensure the minimal gap in a schedule plan, while backfilling allocates the ordering list of tasks and then backfills the holes produced between the allocation using the appropriate tasks. Both strategies do not involve an optimization algorithm that requires the intensive computation, since the WaaS platforms consider speed in scheduling to cope with the users' QoS requirements.

While gap search is related to strategy for improving the resource utilization, another approach utilizes resource type configuration to optimize the cost spent on leasing computational resources. In a heterogeneous environment where resources are leased from third-party providers with some monetary costs (i.e., utility grids, clouds), determining resource type configuration to optimize the cost of leasing resources is necessary. For example, Dyna algorithm (Zhou et al. 2016) that considers the combination use of on-demand and spot instances (i.e., VM pricing schemes) in Amazon EC2, utilizes heuristics to find the optimal resource type configuration to minimize the cost.

4.5 Resource Provisioning Model

Resource provisioning forms an essential pair with task scheduling. In this stage, scheduling algorithms acquire and allocate resources to execute the scheduled tasks. We derive the categorization of resource provisioning based on the ability of scheduling algorithms to expand and shrink the number of resources within the platforms to accommodate the dynamic workloads of WaaS platforms as shown in Figure 7.

4.5.1 Static Provisioning. The *Static provisioning* refers to scheduling algorithms where the number of resources used is relatively static along the scheduling process. Therefore, the primary issue in a static resource provisioning is related to the ability of algorithms to optimize the available resources to accommodate multiple users submitting their workflows into the platforms. This condition can be observed from the algorithms that emphasize heavily on the prioritization technique for workflows to be scheduled due to the limited available resources contested by many users. Another aspect is the improvement of resource utilization of the systems which describes the ability of algorithms to allocate a limited number of resources efficiently.

This static provisioning is not exclusive to the non-virtualized environment (e.g., clusters, grids), where it is evident that the number of resources is hardly changing over time. This case also prevails in cloud computing environments where the WaaS providers determine the number of VMs to be leased before initiating the platforms and the number remains unchanged over the time. In this scenario, the scheduling algorithms do not consider any resource provisioning strategy to scale up and down resources when facing a dynamic workload of workflows.

4.5.2 Dynamic Provisioning. As the clouds provide elastic provisioning of virtual machines, the scheduling algorithms of WaaS platforms in clouds take advantage of *dynamic provisioning* approach. The automated scaling of resources that can be easily implemented in clouds has been widely adopted in scheduling algorithms that deal with a dynamic workload where the need of resources can be high at a point (i.e., peak hours), while at the same time the operational cost must be kept at minimum. To minimize the cost of leasing VMs, they have to be released when the request is low. From the existing algorithms, at least, there are two different approaches to auto-scaling the cloud instances, *workload-aware* and *performance-aware*.

Workload-aware dynamic provisioning is related to the ability of algorithms to become aware of the workload status in WaaS platforms, and then to act according to the situation. For example, acquiring more VMs to accommodate the peak condition. One of the heuristics used in this scenario is based on the deadline constraints of the workload. For example, the algorithms use a task's deadline to decide whether a task should re-use available VMs, provision a new VM that can finish before the deadline, or delay the schedule to re-use future available VMs as long as it does not violate the deadline. This decision is important as the dynamic workload is common in WaaS platforms where the systems cannot predict the future status of the workload. Using this heuristic provisioning additional VMs is more accurate as the acquired new VM is based on the requirement of a particular task being scheduled.

On the other hand, the *performance-aware* dynamic provisioning refers to an approach of auto-scaling the VMs based on total resource utilization of current provisioned VMs. The algorithms monitor the status of the systems and acquire additional VMs when the utilization is high and release several idle VMs when the utilization is low. Maintaining resource utilization at a certain threshold ensures the efficiency of WaaS platforms in the scheduling process. The majority of works considering this approach are the ones that consider only homogeneous VM type in their systems. In this way, the algorithms do not need to perform the complicated selection process of the VM types to be chosen.

5 SURVEY

This section discusses a number of surveyed multiple workflows scheduling algorithms from 2009 to 2018 that are relevant to our study. Each algorithm is classified based on the taxonomy presented in the previous section. Furthermore, the description of the algorithms and their first author affiliation is shown in Table 1 while the classification of existing algorithms is depicted in Table 2, 3, 4, 5, and 6.

5.1 Planner-Guided Scheduling for Multiple Workflows

RANK_HYBD algorithm (Yu and Shi 2008) was introduced to overcome the impracticality of ensemble approach (i.e., merging multiple workflows) to handle different submission time of workflows to the system by scheduling individual tasks dynamically. RANK_HYBD algorithm put together all ready tasks from different workflows into a pool. Then, the algorithm used a modified upward ranking (Topcuoglu et al. 2002) which calculates the weight of a task based on its relative position from the exit tasks and its estimated computational length to assign individual tasks priorities. In contrast with the original upward ranking implementation in HEFT algorithm that chose tasks with higher rank value, RANK_HYBD preferred tasks with the lowest rank in the pool. In this case, HEFT preferred the tasks from later arriving workflows and the tasks with the most extended estimated runtime, which created an unfair pre-emptive policy for the running workflows. By using the opposite approach, RANK_HYBD algorithm avoided the pre-emptive scheduling delay of a nearly finished workflow if a new workflow is submitted in the middle of the execution.

This algorithm was the first solution for multiple workflows scheduling. The approach to tackle dynamic workload of workflows using dynamic prioritization for tasks within a workflow and between workflows has been adopted by many algorithms later. Even though many aspects such as QoS constraints, performance

Table 1. Description of Multiple Workflows Scheduling Algorithms

Algorithms	References	First Author Affiliation	Keyword
RANK_HYBD	(Yu and Shi 2008)	Wayne State University, United States	Dynamic-guided scheduling
MQMW	(Xu et al. 2009)	Shandong University, China	Multi-QoS scheduling
P-HEFT	(Barbosa and Moreira 2011)	Universidade do Porto, Portugal	Dynamic-parallel scheduling
FDWS	(Arabnejad et al. 2014)		Fairness & priority
MW-DBS	(Arabnejad and Barbosa 2017a)		Deadline-budget constraints
DBWS	(Ghasemzadeh et al. 2017)		Deadline-budget constraints
MQ-PAS	(Arabnejad and Barbosa 2017b)		Profit-aware
OWM	(Hsu et al. 2011)	National Chiao-Tung University, Taiwan	Scheduling framework
MOWS	(Wang et al. 2016)		
EDF_BF	(Stavriniades and Karatza 2011)	Aristotle University of Thessaloniki, Greece	Exploit schedule gaps
EDF_BF_IC	(Stavriniades and Karatza 2015)		Data-locality perspective
EDF_BF <i>In-Mem</i>	(Stavriniades et al. 2017)		
OPHC-TR	(Sharif et al. 2014)	The University of Sydney, Australia	Privacy constraint
DGR	(Chen et al. 2015)		Task rearrangement
Adaptive dual-criteria	(Tsai et al. 2015)	National Taichung University of Education, Taiwan	Partition-based scheduling
MLF_ID	(Lin et al. 2016)	Fuzhou University, China	Partition-based scheduling
FASTER	(Zhu et al. 2016)	National University of Defense Technology, China	Fault-tolerant
PRS	(Chen et al. 2016a)		Uncertainty-aware
EONS	(Chen et al. 2016b)		Energy-efficient
EDPRS	(Chen et al. 2017)		Uncertainty-aware
EnReal	(Xu et al. 2016)	Nanjing University, China	Energy-efficient
Dyna	(Zhou et al. 2016)	Nanyang Technological University, Singapore	Cloud spot instances
FSDP	(Wang et al. 2017)	Dalian University of Technology, China	Fairness & priority
F_DMHSV	(Xie et al. 2017a)	Hunan University, China	Fairness & priority
DPMMW&GESMW	(Xie et al. 2017b)		Energy-efficient
CWSA	(Rimal and Maier 2017)	Institut National de la Recherche Scientifique, Canada	Exploiting schedule gaps
EPSM	(Rodriguez and Buyya 2018)	The University of Melbourne, Australia	Container service
MW-HBDCS	(Zhou et al. 2018)	Guangzhou University, China	Deadline-budget constraints

variability, and real workflow applications have not been included in the experiment, this pioneering work became a necessary benchmark for the following algorithms.

5.2 Multiple QoS Constrained for Multiple Workflows Scheduling

Multiple QoS Constrained Scheduling Strategy of Multi-Workflows (MQMW) algorithm (Xu et al. 2009) incorporated a similar strategy of RANK_HYBD to schedule multiple workflows. MQMW prioritized tasks dynamically based on several parameters including resource requirement of a task, time and cost variables, and covariance value between time and cost constraint. The algorithm preferred the tasks with a minimum requirement of resource to execute, minimum time and cost limit, and a task with minimum covariance between its time and cost limit (i.e., when time limit decreases, the cost will highly increase).

MQMW was the first attempt to provide the solution of multiple workflows scheduling on cloud computing environment. It is tested against RANK_HYBD, eventhough the RANK_HYBD was not considered the cost in the scheduling constraint. The results showed that MQMW performs better than RANK_HYBD on the designated environmental model. However, its cloud model was not resembling the real characteristics that are inherent in clouds such as elastic scalability of instances, on-demand resources, pay-as-you-go pricing schemes, and performance variability of cloud environments.

5.3 Fairness in Multiple Workflows Scheduling

Parallel Task HEFT (P-HEFT) algorithm (Barbosa and Moreira 2011) was the first work of a group from the Universidade do Porto. P-HEFT modelled the non-monotonistic tasks (i.e., execution time of a task might differ on different number of resource usage) in their work. The algorithm used relative length position of a task from the entry task (i.e., t-level/top-level) and exit task (i.e., b-level/bottom-level) to assign the priorities between tasks. In their case, the task model was different from other works as it allowed parallel execution of a task in several processors.

The next work from this group was the Fairness Dynamic Workflow Scheduling (FDWS) algorithm (Arabnejad et al. 2014). FDWS chose a single ready task from each workflow into the pool instead of putting all ready tasks together. Local prioritization within a workflow utilized upward rank mechanism while the task selection from different workflows to schedule used a percentage of the remaining task number of workflow the task belongs to (PRT) and a task position in its workflow's critical path (CPL).

Multi-Workflow Deadline-Budget Scheduling Algorithm (MW-DBS) (Arabnejad and Barbosa 2017a) was their work that addressed the utility aspect of a heterogeneous multi-tenant distributed system. This algorithm included deadline and budget as constraints. Furthermore, local priority was assigned using the same method from FDWS. However, instead of using PRT and CPL, MW-DBS used task's deadline and workflow's scheduled tasks ratio for assigning global priority. Finally, MW-DBS modified the processor selection phase, in which it included a budget limit for task processing.

This group also introduced multiple workflows scheduling algorithm for cloud computing environments that was called as Deadline-Budget Workflow Scheduling (DBWS) algorithm (Ghasemzadeh et al. 2017). This algorithm incorporated most of the basic scheduling algorithm structure that resembled FDWS and MW-DBS. Task selection was similar to FDWS while resource selection used deadline and budget as constraints. The deadline and budget were utilized differently, as the algorithm was designed for cloud environments that had a different pricing model compared to the utility grid environments that were used in MW-DBS. In this case, the workflow's deadline was distributed to the tasks using level-based deadline distribution. Hence, the task within the same level will have the same sub-deadline. The sub-deadline was considered as a soft-deadline, so if no resources can satisfy the sub-deadline, the algorithm will consider other resources that allow the earliest finish time instead of rejecting the task. Furthermore, the resources were selected based on their time and cost factor that determined the most efficient pricing (i.e., worthiness).

The latest work on multiple workflow scheduling was the Multi-QoS Profit-Aware Scheduling algorithm (MQ-PAS) (Arabnejad and Barbosa 2017b). MQ-PAS was the extended version of DBWS that was designed not only for cloud computing environment, but also for general utility-based distributed system. Task selection phase adopted MW-DBS component, and DBWS rule of selecting the efficient instances was incorporated in the resource selection phase.

Several variations of multiple workflows scheduling scenarios were covered in their works. One of the specific signatures from this group is the strategy of choosing a single ready task from a workflow to compete in the scheduling cycle with the other workflows. This represents the term "Fairness" that becomes the primary concern in most of their works. However, with their broad scenarios of algorithms that was intended to cover as general as possible the process in a multi-tenant distributed systems, specific requirements in clouds that were different from utility grids (e.g., billing period schemes, dynamic and uncertain environment) were not considered in their works.

5.4 Online Multiple Workflows Scheduling Framework

A group from The National Chiao-Tung University focused on developing a scheduling framework for multiple workflows scheduling. Their first algorithm, called the Online Workflow Management (OWM) (Hsu et al. 2011)

Table 2. Taxonomy of Workload Model

Algorithms	References	Workflow Type		QoS Requirements	
		Homogeneous	Heterogeneous	Homogeneous	Heterogeneous
RANK_HYBD	(Yu and Shi 2008)		✓	✓	
MQMW	(Xu et al. 2009)		✓	✓	
P-HEFT	(Barbosa and Moreira 2011)		✓	✓	
FDWS	(Arabnejad et al. 2014)		✓	✓	
MW-DBS	(Arabnejad and Barbosa 2017a)		✓	✓	
DBWS	(Ghasemzadeh et al. 2017)		✓	✓	
MQ-PAS	(Arabnejad and Barbosa 2017b)		✓	✓	
OWM	(Hsu et al. 2011)		✓	✓	
MOWS	(Wang et al. 2016)		✓	✓	
EDF_BF	(Stavrinides and Karatza 2011)		✓	✓	
EDF_BF_IC	(Stavrinides and Karatza 2015)		✓	✓	
EDF_BF <i>In-Mem</i>	(Stavrinides et al. 2017)		✓	✓	
OPHC-TR	(Sharif et al. 2014)	✓		✓	
DGR	(Chen et al. 2015)		✓	✓	
Adaptive dual-criteria	(Tsai et al. 2015)		✓	✓	
MLF_ID	(Lin et al. 2016)		✓	✓	
FASTER	(Zhu et al. 2016)		✓	✓	
PRS	(Chen et al. 2016a)		✓	✓	
EONS	(Chen et al. 2016b)		✓	✓	
EDPRS	(Chen et al. 2017)		✓	✓	
EnReal	(Xu et al. 2016)		✓	✓	
Dyna	(Zhou et al. 2016)		✓	✓	
FSDP	(Wang et al. 2017)		✓	✓	
F_DMHSV	(Xie et al. 2017a)		✓	✓	
DPMMW&GESMW	(Xie et al. 2017b)		✓	✓	
CWSA	(Rimal and Maier 2017)		✓	✓	
EPSM	(Rodriguez and Buyya 2018)		✓	✓	
MW-HBDCS	(Zhou et al. 2018)		✓	✓	

consisted of four phases, critical path workflow Scheduling (CPWS), task scheduling, multi-processor task rearrangement, and adaptive allocation (AA). The CPWS phase ranked all of the ready tasks based on their relative position in their workflows before they were submitted to scheduling queue to create a schedule plan. If there were some gaps in a schedule plan, task rearrangement took place to fill the gaps to improve resource utilization. Furthermore, AA scheduled the highest priority task from the queue that was constructed based on the near-optimal schedule plan.

In their following work, they extended OWM into Mixed-Parallel Online Workflow Scheduling (MOWS) (Wang et al. 2016). They modified the CPWS phase using the Shortest-Workflow-First (SWS) policy combined with the critical path prioritization. Then, MOWS used the priority-based backfilling to fill the hole of a schedule in the task rearrangement stage. The pre-emptive task scheduling policy was introduced in the AA phase, so the algorithm allowed the system to schedule the shortest workflow with pre-emptive policy and stopped it when the higher priority workflow was ready to run.

Both OWM and MOWS utilized periodic scheduling, in which it periodically created a schedule plan for a set of ready tasks before submitting it to the scheduling queue. In this way, the algorithm can produce better scheduling results without having a compute-intensive optimization beforehand. However, this approach may

still create a bottleneck of pre-processing computation if the number of the ready tasks in the pool increases. Implementing a strategy to create a fairness scenario when selecting ready tasks to reduce the complexity of calculating a schedule plan may work to enhance this scheduling framework.

5.5 Real-time Multiple Workflows Scheduling

One of the active groups that focused on real-time and uncertainty aspects of multiple workflows scheduling was the Stavrinides Group from The Aristotle University of Thessaloniki, Greece. They did impressive works on multiple workflows scheduling that explicitly addressed the uncertainty in cloud computing environments.

Their first work was the Earliest Deadline First with Best Fit (EDF_BF) algorithm (Stavrinides and Karatza 2011). The EDF policy was used for the task selection phase, and the BF component was the strategy for exploiting the schedule gap. EDF_BF incorporated schedule gap exploitation that can be identified through the estimated position of a task's execution in a specified resource. From all of the possible positions, the algorithm exploited the holes using bin packing technique to find the best fit for a task's potential position in a particular resource. Later, the result can also be used to determine which resource should be selected for that particular task.

Another work was the Earliest Deadline First with Best Fit and Imprecise Computation (EDF_BF_IC) algorithm (Stavrinides and Karatza 2015), which extended the previous algorithm with imprecise computation. The imprecise computation was firstly introduced in (Stavrinides and Karatza 2010) to tackle the problem in a real-time environment that was often needed to produce an early proximate result within a specified time limit. The imprecise computation model was implemented by dividing task's components into a mandatory and optional component. A task was considered meeting the deadline if its mandatory part was completed, while the optional component may be fully executed, partially executed, or skipped.

Furthermore, this group explored data-locality and in-memory processing for multiple workflow scheduling (Stavrinides et al. 2017). In this case, they combined EDF_BF algorithm with a distributed in-memory storage solution (i.e., Hercules) to evaluate different way of communication of workflow tasks. They considered two different communication scenarios, communication through a network and via temporary files utilizing the Hercules in-memory storage solution. The results showed that scheduling performance increased when the I/O to computation ratio reduced by using in-memory storage which enforced the locality of data.

Despite the variation, their algorithm's main idea was to schedule all of the ready tasks using EDF policy for resources that can allow the tasks to finish in their earliest time. The algorithm maintained a local queue for each resource, and then, optimized the local allocated queue using gaps filling techniques and, in one of the works, manipulated a small portion of the tasks that may have a little significance (i.e., imprecise computation). Their algorithms were designed for a multi-tenant system with a static number of resources. Therefore, the design may not be suitable for cloud computing environments—in which were suffered most by the uncertainty problems—where the auto-scaling of resources is possible.

5.6 Adaptive and Privacy-aware Multiple Workflows Scheduling

A group from The University of Sydney introduced an excellent work of multiple workflows scheduling that concerned on the privacy of users (Sharif et al. 2014). They developed two algorithms; Online Multiterminal Cut for Privacy in Hybrid Clouds using PCP Ranking (OMPHC-PCPR) and Online Scheduling for Privacy in Hybrid Clouds using Task ranking (OPHC-TR). OMPHC-PCPR was merging multiple workflows into one single workflow before scheduling. Hence, this solution is out of our scope but the other one, OPHC-TR, used an approach that is inclusive of our study. Both algorithms calculated the privacy level of each workflow before they decided to schedule them in private or public clouds. The private clouds were used mainly for the workflow that comprised a high level of privacy parameters. The main differences between the two algorithms were the input. While

Table 3. Taxonomy of Deployment Model

Algorithms	References	Non-virtualized	Virtualized	
			VM-based	Container-based
RANK_HYBD	(Yu and Shi 2008)	✓		
MQMW	(Xu et al. 2009)		✓	
P-HEFT	(Barbosa and Moreira 2011)	✓		
FDWS	(Arabnejad et al. 2014)	✓		
MW-DBS	(Arabnejad and Barbosa 2017a)	✓		
DBWS	(Ghasemzadeh et al. 2017)		✓	
MQ-PAS	(Arabnejad and Barbosa 2017b)		✓	
OWM	(Hsu et al. 2011)	✓		
MOWS	(Wang et al. 2016)	✓		
EDF_BF	(Stavrinides and Karatza 2011)	✓		
EDF_BF_IC	(Stavrinides and Karatza 2015)	✓		
EDF_BF <i>In-Mem</i>	(Stavrinides et al. 2017)	✓		
OPHC-TR	(Sharif et al. 2014)		✓	
DGR	(Chen et al. 2015)	✓		
Adaptive dual-criteria	(Tsai et al. 2015)	✓		
MLF_ID	(Lin et al. 2016)		✓	
FASTER	(Zhu et al. 2016)		✓	
PRS	(Chen et al. 2016a)		✓	
EONS	(Chen et al. 2016b)		✓	
EDPRS	(Chen et al. 2017)		✓	
EnReal	(Xu et al. 2016)		✓	
Dyna	(Zhou et al. 2016)		✓	
FSDP	(Wang et al. 2017)	✓		
F_DMHSV	(Xie et al. 2017a)	✓		
DPMMW&GESMW	(Xie et al. 2017b)		✓	
CWSA	(Rimal and Maier 2017)		✓	
EPSM	(Rodriguez and Buyya 2018)		✓	
MW-HBDCS	(Zhou et al. 2018)	✓		

OMPHC-PCPR considered a merged single workflow from several workflows, OPHC-TR processed each task using a rank mechanism to decide which tasks were submitted into the scheduling queue.

Another work from this group was the DGR algorithm (Chen et al. 2015). This algorithm used heuristics, which started the solution with the initial reservation of resources for scheduling particular tasks. During the execution, uncertainty (i.e., performance and execution time variation) may profoundly affect the initial reservation and break the schedule plan. In this case, the algorithm rescheduled the tasks to handle the broken reservation. DGR utilized task rearrangement techniques and exploited a dynamic search tree to fix this reservation.

The privacy constraint is an essential aspect that has been tackled in the OPHC-TR by separating the execution in a private and public cloud. However, it is important to consider the security aspect in managing the privacy, since both aspects are highly inter-related. One of the workflow scheduling algorithms that consider security is the SABA algorithm (Zeng et al. 2015). However, it is designed for a single workflow scheduling and intended to explore the relationship between cost and security aspects in the scheduling, instead of focusing on privacy

aspect. Further exploration of privacy and security in the multiple workflows scheduling has to be done as it resembles the real world workflow application problems in multi-tenant distributed systems.

5.7 Adaptive Dual-criteria Multiple Workflows Scheduling

Another adaptive approach in scheduling multiple workflows was an adaptive dual-criteria algorithm (Tsai et al. 2015). This algorithm used heuristics that utilized scheduling adjustment via task rearrangement. An essential approach to this algorithm was the clustering of tasks, and treated them as an integrated set in scheduling to minimize the critical data movement within tasks. Hence, any re-arrangement or adjustment to fill the schedule holes involved the set of tasks to be moved.

Since the approach used was the periodic scheduling, the frequency of scheduling cycle becomes critical. Infrequent scheduling cycle implies to the larger set of tasks to be processed which may result in a more optimized scheduling plan but potentially required a more intensive computation for creating the plan. Meanwhile, a frequent cycle may fasten the scheduling plan computation due to its size of tasks, but may possibly reduce the quality of a schedule. This variation was not being addressed and explored in-depth by the authors. Besides, the treatment of a cluster of tasks increases the coarse-granularity of scheduling that may widen the gaps produced. In this way, the task re-arrangement may hardly find the holes that can be fit by a coarse-grained set of clustered tasks.

5.8 Multiple Workflows Scheduling on Hybrid Clouds

Another work designed for hybrid cloud environments was the Minimum-Load-Longest-App-First with the Indirect Transfer Choice (MLF_ID) (Lin et al. 2016). The term Load-Longest-App had a similar concept to the critical path. So, MLF_ID was a heuristic algorithm that incorporated the workflows prioritization based on their critical path and exploited the use of private clouds before leasing the resources in public clouds. MLF_ID partitioned the workflow based on a hierarchical iterative application partition (HIAP) to eliminate data dependencies between a set of tasks by clustering tasks with dependencies into the same set before scheduling them into either private or public clouds.

The use of hybrid clouds in this work was emphasized to extend the computational capacity when the available on-premises (i.e., private clouds) was not enough to serve the workloads. Firstly, the tasks were scheduled to the private clouds, and whenever the capacity was not possible to process, they were being transferred to public clouds. Even though the tasks had been partitioned to make sure that the data transfer between them was minimum, the decision to transfer to public clouds evoked a possible transfer overhead problem. Therefore, some improvements can be made by implementing a policy to decide whether a set of tasks was considered impractical to process in private clouds that include some intelligence, which can be designed to predict the possible overhead in the future of the system. In this way, instead of directly transferring the execution to the public clouds that incites not only additional cost but also the transfer overhead, the algorithm can decide whether it should transfer the execution or delay the process waiting the next available resources.

5.9 Proactive and Reactive Scheduling for Multiple Workflows

Another group that focused on real-time and uncertainty problems in scheduling was the Zhu Group from The National University of Defense Technology, China. They proposed the algorithms that dynamically exploited proactive and reactive methods in a multiple workflows scheduling.

Their first work was Proactive Reactive Scheduling (PRS) algorithm (Chen et al. 2016a). The proactive phase calculated the estimated earliest start and the finished time of tasks and then schedule them dynamically based on a simple list-based heuristic. This method had been incorporated into many algorithms for multiple workflows scheduling. However, using only proactive method was unable to tackle the uncertainties (e.g., performance

Table 4. Taxonomy of Priority Assignment

Algorithms	References	Application Type	QoS Constraint	User-defined	Workflow Structure
RANK_HYBD	(Yu and Shi 2008)				✓
MQMW	(Xu et al. 2009)		✓		
P-HEFT	(Barbosa and Moreira 2011)				✓
FDWS	(Arabnejad et al. 2014)				✓
MW-DBS	(Arabnejad and Barbosa 2017a)		✓		✓
DBWS	(Ghasemzadeh et al. 2017)		✓		✓
MQ-PAS	(Arabnejad and Barbosa 2017b)		✓		✓
OWM	(Hsu et al. 2011)				✓
MOWS	(Wang et al. 2016)				✓
EDF_BF	(Stavriniades and Karatza 2011)		✓		
EDF_BF_IC	(Stavriniades and Karatza 2015)		✓		
EDF_BF <i>In-Mem</i>	(Stavriniades et al. 2017)		✓		
OPHC-TR	(Sharif et al. 2014)	✓	✓		
DGR	(Chen et al. 2015)		✓		
Adaptive dual-criteria	(Tsai et al. 2015)		✓		✓
MLF_ID	(Lin et al. 2016)		✓		
FASTER	(Zhu et al. 2016)		✓		
PRS	(Chen et al. 2016a)		✓		
EONS	(Chen et al. 2016b)				
EDPRS	(Chen et al. 2017)		✓		
EnReal	(Xu et al. 2016)		✓		
Dyna	(Zhou et al. 2016)		✓		
FSDP	(Wang et al. 2017)		✓		
F_DMHSV	(Xie et al. 2017a)				✓
DPMMW&GESMW	(Xie et al. 2017b)		✓		
CWSA	(Rimal and Maier 2017)		✓		
EPSM	(Rodriguez and Buyya 2018)		✓		
MW-HBDCS	(Zhou et al. 2018)		✓		✓

variation, overhead delays) that led to sudden changes in the system. Then, PRS algorithm introduced a reactive phase whenever two disruptive events occurred (i.e., the arrival of a new workflow and finishing time of a task). The reactive phase was triggered by two disruption events to re-do (i.e., update) the scheduling process based on the latest system status.

They then extended the PRS into Event-driven and Periodic Rolling Strategies (EDPRS) algorithm (Chen et al. 2017). EDPRS tackled a flaw in the PRS algorithm, that, if none of the two disruption events happened, the scheduling process could not be pushed forward. They introduced a periodic rolling strategy (i.e., scheduling cycle) that drove the re-iteration of the schedule. In this way, even though no disruption events occurred, the algorithm repeated their scheduling activities after a specific periodic rolling time. Both PRS and EDPRS worked well in handling the uncertainty in cloud computing environments.

This group also worked on energy-efficient multiple workflow scheduling algorithms. Their work was the Energy-Efficient Online Scheduling Algorithm (EONS) (Chen et al. 2016b). EONS was different from the other energy-efficient scheduling algorithms due to its focus on fast and real-time oriented scheduling. EONS utilized simple auto-scaling techniques to lower the energy consumption instead of optimizing the energy usage using techniques such as VM live migration and VM consolidation. The scaling method used simple heuristics that considered the load of the physical host and the hardware efficiency.

Another exciting work from this group addressed the failure in a multiple workflows scheduling. The algorithm, called FASTER, (Zhu et al. 2016) utilized primary backup technique to handle the failure. To the best of our knowledge, this was the only fault-tolerant algorithm for multiple workflows scheduling. They scheduled two copies of a task whenever the task was submitted to the system (i.e., primary and backup copy). The task was considered successful when both primary and backup copies were successfully executed. FASTER also employed auto-scaling resources since the algorithm needed almost double in volume resources due to the primary backup strategy.

The algorithms emphasize a specific strategy to handle real-time scenario by using an immediate scheduling approach which includes the update strategy to adapt to changes dynamically. However, this dynamic approach, especially on the energy-efficient problem, can be improved by optimizing the VM placement on the physical machine since the algorithms that work on energy consumption may have access to the raw computational infrastructure.

5.10 Energy Aware Scheduling for Multiple Workflows

A group from Nanjing University, China proposed algorithm for multiple workflows scheduling that was called EnReal—an energy-aware resource allocation method for workflow in the cloud environment (Xu et al. 2016). While the previous energy-aware algorithm—EONS—utilized auto-scaling techniques to lower the energy consumption, EnReal exploited the VM live migration-based policy. The algorithm partitioned all of the ready tasks in the scheduling queue based on their requested start time and allocated them to the resources on the same physical machine. The adjustment was made whenever a load of the physical machine was exceeding the threshold, and then, VM live migration policy took place.

EnReal also adjusted the VM allocation dynamically whenever a task was finished. Combined with the physical machine resource monitoring, the global resource allocation method emphasized the energy saving of the platform. However, the partitioning method in EnReal did not consider the data dependencies between the tasks that implies for a data transfer overhead between tasks when they were allocated to different physical machines. The energy-aware resource allocation policy in EnReal should have complemented by an ability to aware of data-locality. This policy will not only minimize the energy consumption but also improves the scheduling results in term of total execution cost and makespan.

5.11 Monetary Cost Optimization for Multiple Workflows on Commercial Clouds

A group from the National University of Singapore, proposed Dyna (Zhou et al. 2016), an algorithm that concerned on the clouds dynamicity nature. They introduced a probabilistic guarantee of any defined SLAs of workflow users as it was the closest assumption to uncertainty environment in clouds. This was a novel contribution since the majority of the works assumed deterministic SLAs in their algorithms. Dyna aimed to minimize multiple workflows scheduling execution cost by utilizing VMs with spot instances pricing scheme in Amazon EC2 along with its on-demand instances. Dyna started with the initial configuration of different cloud instance types and refined the configuration iteratively to get the better scenario that minimizes the cost while meeting the deadline.

Dyna presented an exploration of possible cost reduction in executing multiple workflows by utilizing the spot instances in Amazon EC2. Since WaaS platforms that were assumed in their work acted as a service provider for many users, the use of reserved instances in Amazon EC2 may further reduce the cost of running WaaS. Comparison between on-demand, spot, and reserved instances in Amazon EC2 needs to be done further to deepen the plausible scenario on minimizing the execution cost of multiple workflows in clouds.

Table 5. Taxonomy of Task Scheduling

Algorithms	References	Immediate Scheduling	Periodic Scheduling	
			Gap Search	Configuration Search
RANK_HYBD	(Yu and Shi 2008)	✓		
MQMW	(Xu et al. 2009)	✓		
P-HEFT	(Barbosa and Moreira 2011)	✓		
FDWS	(Arabnejad et al. 2014)	✓		
MW-DBS	(Arabnejad and Barbosa 2017a)	✓		
DBWS	(Ghasemzadeh et al. 2017)	✓		
MQ-PAS	(Arabnejad and Barbosa 2017b)	✓		
OWM	(Hsu et al. 2011)		✓	
MOWS	(Wang et al. 2016)		✓	
EDF_BF	(Stavrinides and Karatza 2011)		✓	
EDF_BF_IC	(Stavrinides and Karatza 2015)		✓	
EDF_BF <i>In-Mem</i>	(Stavrinides et al. 2017)		✓	
OPHC-TR	(Sharif et al. 2014)	✓		
DGR	(Chen et al. 2015)		✓	
Adaptive dual-criteria	(Tsai et al. 2015)		✓	
MLF_ID	(Lin et al. 2016)	✓		
FASTER	(Zhu et al. 2016)		✓	
PRS	(Chen et al. 2016a)	✓		
EONS	(Chen et al. 2016b)	✓		
EDPRS	(Chen et al. 2017)	✓		
EnReal	(Xu et al. 2016)			✓
Dyna	(Zhou et al. 2016)			✓
FSDP	(Wang et al. 2017)	✓		
F_DMHSV	(Xie et al. 2017a)		✓	
DPMMW&GESMW	(Xie et al. 2017b)		✓	
CWSA	(Rimal and Maier 2017)		✓	
EPSM	(Rodriguez and Buyya 2018)	✓		
MW-HBDCS	(Zhou et al. 2018)	✓		

5.12 Fairness Scheduling for Multi-Workflows

Fairness Scheduling with Dynamic Priority for Multi Workflow (FSDP) (Wang et al. 2017) was an algorithm proposed by a group from Dalian University of Technology, China. FSDP emphasized the fairness aspect as it incorporated *slowdown* metrics to their algorithm’s policy. *Slowdown* value was the ratio of the makespan of a workflow when it was being scheduled in a dedicated service to the makespan of it being scheduled in a shared environment with the other workflows. The closest *slowdown* to 1, the fairest the algorithm scheduled the workflows in the system. FSDP also included *urgency* metric, a value that represented the priority of each workflow based on its deadline. The *slowdown* and *urgency* was updated periodically when a workflow finished ensuring the refinement in the scheduling process.

However, the fairness scenario was not explored in-depth by the authors. FSDP algorithm is only evaluated using two different workflows on a various number of resources (i.e., processor). The issue of fairness would arise when the number of submitted workflows was high enough to represent the condition of peak hour in multi-tenant distributed systems.

5.13 Scheduling Trade-off of Dynamic Multiple Workflows

A group from Hunan University presented two algorithms for multiple workflows scheduling. The first one was the Fairness-based Dynamic Multiple Heterogeneous Selection Value (F_DMHSV) (Xie et al. 2017a). The algorithm consisted of six steps which were task prioritization, task selection, task allocation, task scheduling, the arrival of new workflow handling, and task monitoring. The task prioritization used a descending order of heterogeneous priority rank value (HPRV) (Xie et al. 2014), which included the out-degree (i.e., number of successors) of the task. The task was selected from the ready tasks pool based on the maximum HPRV. Furthermore, the task was allocated to the processor with minimum heterogeneous selection value (HSV) (Xie et al. 2014) that optimized the task allocation criteria using the combination of upward and downward rank. The task, then, was scheduled to the earliest available processor with minimum HSV.

In the same year, this group published energy-efficient algorithms for multiple workflows scheduling, which combined the Deadline-driven Processor Merging for Multiple Workflow (DPMMW) that aimed to meet the deadline, and the Global Energy Saving for Multiple Workflows (GESMW) aimed to lower the energy consumption (Xie et al. 2017b). DPMMW was a clustering algorithm which allocated the clustered tasks in a minimum number of processors, so the algorithm can put idle processors into sleep mode. Meanwhile, GESMW reassigned and adjusted the tasks to any processor with minimum energy consumption in the global scope. The combination of DPMMW&GESW was exploited to get a lower energy consumption. This approach was different from the previous two energy-efficient algorithms that focused on virtual machine level manipulation.

This group presented two opposite approaches to a scheduling with different objectives. However, in both approaches, the works emphasize on a similar strategy of the resource selection. In their first work, the algorithm focuses on selecting various resources to minimize the makespan, while in the second one, it is selecting different machine with various energy efficiency to minimize the energy consumption. These resource selection strategies can improve the scheduling result by combining them with efficient task scheduling approaches.

5.14 Workflow Scheduling in Multi-Tenant Clouds

Another algorithm for multiple workflows scheduling was Cloud-based Workflow Scheduling (CWSA) (Rimal and Maier 2017). The algorithm was intended for compute-intensive workflows applications. Hence, CWSA ignored data-related overhead and focused on compute resource management. The algorithm aimed to minimize the total makespan of the workflows which in result, minimizing the cost of execution. CWSA was an extension to multi-tenant workflow management system (Rimal and El-Refaey 2010) which exploited the schedule gap. If there was no gap found in the initial workflow schedule, FCFS, EASY Backfilling, and MCT algorithms were used to schedule the tasks instead of the CWSA algorithm.

However, CWSA did not further optimize their cost minimization strategy using a specific cost-aware resource provisioning technique. CWSA auto-scaled the resources using a resource utilization threshold, in which it acquired and released the resources if their utilization exceeded or was below a specific number. For example, they implemented the rule such as if the utilization was $\geq 70\%$ for 10 minutes, then it was scaled-up by adding 1 VM of small size. In this case, the algorithms with cost-aware auto-scaling strategy—that specifically acquires and releases particular VMs based on the workload—may outperform CWSA that only considers overall system utilization based auto-scaling. This type of auto-scaling strategy is not provisioning resources that are specifically tailored to the need of the workloads.

5.15 Multi-tenant Workflow as a Service Platform

The latest solution for multiple workflow scheduling was Elastic Resource Provisioning and Scheduling Algorithm for Multiple Workflows designed for Workflow as a Service Platforms (EPSM) (Rodriguez and Buyya 2018). The

Table 6. Taxonomy of Resource Provisioning

Algorithms	References	Static Provisioning	Dynamic Provisioning	
			Workload-aware	Performance-aware
RANK_HYBD	(Yu and Shi 2008)	✓		
MQMW	(Xu et al. 2009)	✓		
P-HEFT	(Barbosa and Moreira 2011)	✓		
FDWS	(Arabnejad et al. 2014)	✓		
MW-DBS	(Arabnejad and Barbosa 2017a)	✓		
DBWS	(Ghasemzadeh et al. 2017)		✓	
MQ-PAS	(Arabnejad and Barbosa 2017b)	✓		
OWM	(Hsu et al. 2011)	✓		
MOWS	(Wang et al. 2016)	✓		
EDF_BF	(Stavrinides and Karatza 2011)	✓		
EDF_BF_IC	(Stavrinides and Karatza 2015)	✓		
EDF_BF <i>In-Mem</i>	(Stavrinides et al. 2017)	✓		
OPHC-TR	(Sharif et al. 2014)		✓	
DGR	(Chen et al. 2015)	✓		
Adaptive dual-criteria	(Tsai et al. 2015)	✓		
MLF_ID	(Lin et al. 2016)		✓	
FASTER	(Zhu et al. 2016)		✓	
PRS	(Chen et al. 2016a)		✓	
EONS	(Chen et al. 2016b)		✓	
EDPRS	(Chen et al. 2017)		✓	
EnReal	(Xu et al. 2016)		✓	
Dyna	(Zhou et al. 2016)		✓	
FSDP	(Wang et al. 2017)	✓		
F_DMHSV	(Xie et al. 2017a)	✓		
DPMMW&GESMW	(Xie et al. 2017b)		✓	
CWSA	(Rimal and Maier 2017)			✓
EPSM	(Rodriguez and Buyya 2018)		✓	
MW-HBDCS	(Zhou et al. 2018)	✓		

algorithm introduced scheduling algorithm for WaaS that utilized a container to bundle workflow’s application before deploying it into VMs. In this way, the users can share the same VMs without having any problem related to software dependencies and libraries.

The algorithm consisted of two-phase, resource provisioning which included a flexible approach of scaling up and down the resources to adapt dynamic workload of workflows, and scheduling which exploited a delay policy based on the task’s deadline to re-use the cheapest resources as much as possible to minimize the cost. In the resource provisioning phase, EPSM incorporated an overhead detection in the form of provisioning delay (i.e., acquisition delay) and deprovisioning delay (i.e., release delay) of the VMs. This was proven to be able to reduce unnecessary cost due to violating a coarse-grain billing period of clouds. The algorithm made an update of unscheduled tasks’ deadline whenever a task finished the execution. In this way, the algorithm dynamically adapted the gap between the estimated and actual execution plan to ensure the scheduling objectives. In the scheduling phase, EPSM considered re-using available VMs before provisioning the new one to minimize the delay overhead of acquiring new VMs and possible cost minimization by re-using the cheapest VMs available.

5.16 Concurrent Multiple Workflows Scheduling

The latest work on deadline- and budget-constrained multiple workflows scheduling was Multi-workflow Heterogeneous budget-deadline-constrained Scheduling (MW-HBDCS) algorithm (Zhou et al. 2018) that was introduced by a group from Guangzhou University, China. MW-HBDCS algorithm was designed to improve the flaw on the previous similar algorithm, MW-DBS. Significant enhancement was the inclusion of budget in the ranking process to prioritize the tasks for scheduling. MW-HBDCS was also designed to tackle uncertainties in the environments. In this work, the authors used the terms "consistent" and "inconsistent" environments to describe various dynamicity in multi-tenant distributed systems.

MW-HBDCS tackled many flaws that were not considered in the previous deadline- and budget-constrained scheduling algorithms. These enhancements were the model of multi-tenant distributed systems that incorporated high uncertainties and dynamicity, the improvement of task's ranking mechanism that enclosed the budget as one of the primary constraints besides the deadline—while previously only acted as a complementary constraint—, and the various scenarios on both synthetic and real-world workflow applications. Since the authors were highly considered the budget as crucial as the deadline, it is essential to include the trade-off analysis between the values of budget and deadline related to the success rate of workflows execution. One of the techniques to such an approach is the Pareto analysis that is used for multi-objective workflow scheduling (e.g., MOHEFT (Durillo et al. 2012)). Furthermore, this algorithm considers static resource provisioning. Therefore, it may not achieve optimal performance in cloud computing environments where the auto-scaling of resources is possible.

6 FUTURE DIRECTIONS

This section describes the future direction of multiple workflows scheduling in multi-tenant distributed systems. We capture the future direction of multi-tenancy in multiple workflows scheduling from existing solutions and rising trend technologies that have a high potential to support the enhancement of multi-tenant platforms. The range is broad—from the pre-processing phase which involves the strategy to accurately estimate task execution time that is a prerequisite for scheduling process; scheduling techniques that are aware of constraints such as failure, deadline, budget, energy usage, privacy, and security; to the use of heterogeneous distributed systems that differ not only in capacity but also pricing scheme and provisional procedures. We also observe a potential use of several technologies to enhance the multi-tenancy that comes from the rising trend technologies such as containers, serverless computing and the broad adoption of Internet of Things (IoT) workflows.

6.1 Task Runtime Estimation

Predicting task runtime in clouds is non-trivial, mainly due to the problem in which clouds resources are subject to performance variability (Jackson et al. 2010). This variability occurs due to several factors—including virtualization overhead, multi-tenancy, geographical distribution, and temporal aspects (Leitner and Cito 2016)—that affect not only computational performance but also the communication network (Shea et al. 2014) used to transfer input/output data. The majority of algorithms rely on the estimation of tasks execution time in particular resources to produce an accurate schedule plan. Meanwhile, the works on task runtime estimation in scientific workflows are limited including the latest works by Pham et al. (Pham et al. 2017) and Nadeem et al. (Nadeem et al. 2017) that used machine learning techniques while previously, a work on scientific workflows profiling and characterization by Juve et al. (Juve et al. 2013) that produced a synthetic workflows generator is being used by the majority of works on workflow scheduling. The future task runtime prediction techniques must be able to address dynamic workloads in WaaS platforms that are continuously arriving in resemblance with stream data processing.

6.2 Anomaly Detection and Fault-tolerant Algorithms

Detecting anomaly in scientific workflows is one of the methods to ensure fault-tolerance of multiple workflows scheduling in multi-tenant distributed systems. Several notable works in workflows anomaly detection are presented by Gaikwad et al. (Gaikwad et al. 2016) that used Autoregression techniques to detect the anomalies by monitoring the systems and a similar work by Rodriguez et al. (Rodriguez et al. 2018) that adopted Neural Network methods. On the other hand, the fault-tolerant algorithms found in our survey used replication technique (Zhu et al. 2016) and checkpointing (Zhou et al. 2016) to handle failure in workflows execution. Future works on this area include the integration of detecting anomalies and failure-aware scheduling in WaaS platforms and the use of various fault-tolerant methods in failure-aware algorithms, such as resubmission and live migration.

6.3 Reserved vs. On-demand vs. Spot Instances

The reduction of operational cost has been a long existing issue in utility-based multi-tenant distributed systems. Notably, in cloud computing environments where the resources are leased from third-party providers based on various pricing schemes, cost-aware scheduling is highly considered. While most of the algorithms for cloud computing environments use on-demand instances which ensure the reliability in a pay-as-you-go pricing model, a work by Zhou et al. (Zhou et al. 2016) explored the use of spot instances that is relatively cheaper than on-demand, but less reliable as they were only available for a limited time and could be terminated by the providers. This raises a fault-tolerant issue to be considered in scheduling. On the other hand, as multiple workflows scheduling involves a high number of workflow execution, the use of reserved instances in clouds should be explored to minimize further the total WaaS operational cost. The issue of using reserved instances is how accurate the algorithms can predict the workload of workflows to lease some reserved instances in WaaS platforms. This combination of reserved, on-demand, and spot instances must be explored to create an efficient resource provisioning strategy in multi-tenant distributed systems.

6.4 Budget-constrained Scheduling

The flexibility and ability to easily scale the number of resources (i.e., VMs) in cloud computing environment, leads to a trade-off between two conflicting Quality of Service (QoS) requirements: time and cost. In this case, the more powerful VMs capable of processing a task faster will be more expensive than the slower less powerful ones. There has been an extensive research (Rodriguez and Buyya 2017) on this scheduling topic that specifically designed for cloud computing environments, with most works proposed algorithms that were aimed to minimize the total execution cost while finishing the workflow execution before a user-defined deadline. Meanwhile, the works that aimed to minimize the makespan by fully utilizing the available budget to lease as much as possible the faster resources are limited. We identified algorithms that considered budget in their scheduling such as (Arabnejad and Barbosa 2015), (Ghasemzadeh et al. 2017), (Arabnejad and Barbosa 2017b), and (Zhou et al. 2018) that exploited the workflow budget as a complementary constraint to the deadline. Therefore, none of them aims to fully utilize the available budget to get a faster execution time.

6.5 Multi-clouds and Hybrid Clouds

The use of multi-cloud providers for executing scientific workflows was explored by Jrad et al. (Jrad et al. 2013) and Montes et al. (Montes et al. 2014) by introducing algorithms that were aware of different services available from several providers. However, the only relevant works found in our study are the use of hybrid clouds for separating tasks execution based on some properties instead of multi-clouds. Furthermore, a work used hybrid clouds to treat tasks with different privacy level in healthcare services, while another work utilized public clouds to cover the computational need that could not be fulfilled using private clouds and on-premises infrastructure. In our opinion, further utilization of multi-clouds can benefit WaaS providers since the high requirements of

resources in multi-tenant platforms may not be served by a single cloud provider. The other advantage of multi-clouds is the reduction of operational cost as various cloud providers employed different price for the datacenter in different geographical location. In this way, discovering relevant services can be further exploited to minimize data movements by choosing a handy datacenter location and also comparing the best ratio of price and performance from various cloud instances from multiple cloud providers.

6.6 Energy-efficient Computing

The issue of green computing in clouds has been extensively explored by Beloglazov et al. (Beloglazov et al. 2011). There are several works of multiple workflows scheduling in our study that addressed this energy-efficient issue. A work discussed energy-efficient strategy at the infrastructure level by implementing a live migration technique for scheduling (Xu et al. 2016), while another work tackled the problem at workload level by allocating the load to specific physical machines (Chen et al. 2016b). For WaaS providers that rely on IaaS clouds for their source to lease the computational resources, adopting workload level strategies for energy-aware scheduling is the possible way as they do not have the control over the raw computational infrastructures as IaaS cloud providers do.

6.7 Privacy-aware Scheduling

It is interesting to find a work that addressed the issue of privacy in multiple workflows scheduling (Sharif et al. 2014). This is tackled by separating the execution of tasks on the different type of infrastructures (i.e., hybrid clouds) based on their level of privacy represented in the processed data. Another way to deal with privacy is by adopting a reliable security protocol for data processing in cloud environments, such as a homomorphic encryption (Zhao et al. 2014). However, the increase in security must have influenced the computational time, and this becomes a scheduling challenge to address.

6.8 Microservices for Multi-tenancy

Microservice is a variant of service-oriented architecture (SOA) that has a unique lightweight or even simple protocol and treated the application as a collection of loosely coupled service. We can consider container technology and serverless computing (i.e., function as a service) to fall into the microservices.

Kozhirbayev and Sinnott (Kozhirbayev and Sinnott 2017) report that the performance of a container on a bare metal machine is comparable to a native environment since no significant overhead recording is produced in the runtime. It is a promising technology to enhance multi-tenancy features for multiple workflows scheduling as it can be used as an isolated environment for workflow application before deploying it into virtual machines in clouds. This is because using a virtual machine as an isolated environment eliminates the possibility of sharing its computational capacity between different workflow applications that may have different software dependencies. We argue that, in the future, this technology will be widely used for solving multi-tenancy problem as it has been explored for executing a single scientific workflow as reported in several studies (Gerlach et al. 2015), (Qasha et al. 2016), (Liu et al. 2016), (Hung et al. 2017), (Alzahrani et al. 2017).

Another promising technology is serverless computing (i.e., Function as a Service). This is a new terminology that stands on the top of cloud computing as a simplified version of virtualization service. In this way, cloud providers directly manage resource allocation, and the users only needed to pay for the time of resource usage. This technology facilitates the users who only need to run specific tasks from a piece of code without having a headache in managing the cloud instances. We consider to include this into the future directions since the potential of its multi-tenancy service is high to accommodate the multi-tenant workflows scheduling. Furthermore, this technology has been tested for a single scientific workflows execution as reported by Jiang et al. (Jiang et al. 2017) and Malawski et al. (Malawski et al. 2017). Notably, this function as a service can serve the workloads that consist of platform-independent workflows, which can be efficiently executed on top of this facility without having to provision a new virtual machine.

6.9 Internet of Things (IoT) Workflows

A vision paper by Gubbi et al. (Gubbi et al. 2013) mentions an essential and future use of the Internet of Things (IoT) in a workflow form. The idea, then, has been implemented in several works, including a disaster warning system (Viriyasitavat et al. 2014), a smart city system (Doukas and Antonelli 2014), and big data framework (Nardelli et al. 2017). This type of workflow increases in numbers and its broad adoption is predicted to be widely seen shortly. In the meantime, therefore, the need for a multi-tenant platform that can handle such workflows may arise. The computational characteristics of IoT workflows are different from regular workflows. Moreover, IoT applications are highly demanding network resources to handle end-to-end services from sensors at one point, to users at the other end. Therefore, a specific problem related to network-intensive requirements such as bandwidth-aware and latency-aware must be considered in the scheduling algorithms for IoT workflow application.

7 SUMMARY

This paper presents a study on algorithms for multiple workflows scheduling in multi-tenant distributed systems. In particular, the study focuses on the heterogeneity of workloads, the model for deploying multiple workflows, the priority assignment model for multiple users, the scheduling techniques for multiple workflows, and the resource provisioning strategies in multi-tenant distributed systems. It presents a taxonomy covering the focus of study based on a comprehensive review of multiple workflows scheduling algorithms. The taxonomy is accompanied by classification from surveyed algorithms to show the existing solutions for multiple workflows scheduling in various aspects. The existing algorithms within the scope of the study are reviewed and classified with the aim to open up the problems in this area and provide the readers with a helicopter view on multiple workflows scheduling. Some descriptions and discussions of various solutions are also covered in this paper to provide a more detailed and comprehensive understanding of the state-of-the-art techniques and also to get an insight on further research and development in this area.

ACKNOWLEDGMENTS

This research is partially supported by LPDP (Indonesia Endowment Fund for Education) and ARC (Australia Research Council) research grant.

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