Adaptive Resource Allocation and Consolidation for Scientific Workflow Scheduling in Multi-Cloud Environments

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ABSTRACT The emerging multi-cloud environments (MCEs) empower the execution of large-scale scientific workflows (SWs) with sufficient resource provisioning. However, due to complex task dependencies in SWs and various cost-performance of cloud resources, the SW scheduling in MCEs faces huge challenges. To address these challenges, we propose an Online Workflow Scheduling algorithm based on Adaptive resource Allocation and Consolidation (OWS-A2C). In OWS-A2C, the deadline reassignment is first executed for SW tasks based on the execution performance of instance resources, which enhances resource utilization from a local perspective when executing an SW. Next, the execution instances are allocated and consolidated according to the performance requirements of multiple SWs, which improves resource utilization and reduces the total costs of executing multiple SWs from a global perspective. Finally, the SW tasks are dynamically scheduled to the execution instances with the earliest-deadline-first (EDF) discipline and completed before their sub-deadlines. The extensive simulation experiments are conducted to demonstrate the effectiveness of the proposed OWS-A2C on SW scheduling in MCEs, which outperforms three baseline scheduling methods with higher resource utilization and lower execution costs under deadline constraints.

INDEX TERMS Multi-cloud environments, scientific workflows, scheduling optimization, resource allocation, resource consolidation.

I. INTRODUCTION

In recent years, workflow technologies have been widely adopted by many applications in science domains to handle the data analysis and processing for scientific innovation and knowledge discovery [1], [2]. However, due to the ever-increasing data volumes, the performance requirements of many scientific workflows (SWs) on data analysis and processing have significantly increased and thus their executions have been alternatively migrated to the cloud with more powerful computational capacity [3]–[5]. Furthermore, multi-cloud environments (MCEs) have emerged as a new and efficient computing pattern for large-scale SWs [6]–[8], which offer more sufficient resource provisioning and diversified pricing mechanisms. Thus, the MCEs promise a larger optimization space for SW scheduling [9]. However, SWs contain complicated structures with complex task dependencies [10], while the cost-performance of instance resources for executing the same task might be different in MCEs [11]. Therefore, SW scheduling in MCEs can be regarded as an NP-hard problem [12].

In response to this problem, it is necessary to design an effective scheduling strategy to reduce the execution costs of executing SWs while meeting the Quality-of-Service...
(QoS) requirements. However, most of the current scheduling strategies in cloud environments focus on a single workflow [13]–[16], and they do not fully consider the problem of irregular arrivals in large-scale SW scheduling. Moreover, most of these strategies do not well take some essential constraints into account. For example, the deadline constraint is an important feature in the field of emergency scientific computing [17]. In addition, the existing work mainly depends on the static SW scheduling without the consideration of a real-time manner [18], [19]. Therefore, online scheduling for large-scale SWs with deadline constraints in MCEs has become one of the major challenges in the domain of scientific computing [20].

To address the above challenges, in light of our previous work [21], we propose an Online Workflow Scheduling algorithm based on Adaptive resource Allocation and Consolidation (OWS-A2C). The OWS-A2C aims to improve resource utilization and reduce the execution costs of SWs under deadline constraints in MCEs. The main contributions of this paper are summarized as follows.

- The deadline reassignment is first implemented according to the execution performance of instance resources. From a local perspective, it can improve resource utilization when executing an SW. Next, the execution instances are allocated and consolidated based on the performance requirements of multiple SWs. From a global perspective, it can enhance resource utilization and reduce the total costs of executing multiple SWs. Finally, the SW tasks are dynamically scheduled to the execution instances with the EDF discipline while meeting their deadline constraints.
- Extensive simulation experiments are conducted to demonstrate the effectiveness of the proposed OWS-A2C on SW scheduling in MCEs. The results show that the proposed method can achieve higher resource utilization and lower execution costs than three baseline scheduling methods under deadline constraints.

The rest of this paper is organized as follows. In Section II, we review the related work. Section III formulates the problem of SW scheduling in MCEs. In Section IV, we present the proposed OWS-A2C method in detail. Section V evaluates the proposed method by simulation experiments. In Section VI, we conclude this paper and look for future work.

II. RELATED WORK

As an effective measure for optimizing scientific computing, workflow scheduling has attracted much research attention, while many scholars have contributed to addressing this important problem. In this section, we review the related work on workflow scheduling problem with deadline constraints.

Towards a single workflow, Sakellariou et al. [14] proposed a scheduling algorithm for optimizing costs with budget constraints in grid environments, which can adjust the scheduling plan to approach the optimal one by using the most cost-effective allocation strategy. The algorithm has a certain enlightening effect on our proposed work, but it focused on grid environments without considering the resource pricing mechanisms in cloud computing. Abrishami et al. [15] extended the workflow scheduling scenarios from the grid to cloud environments and designed two workflow scheduling algorithms, including the IaaS Cloud Partial Critical Paths (IC-PCP) and the IaaS Cloud Partial Critical Paths with Deadline Distribution (IC-PCPD2). This work considered some characteristics of cloud computing, such as on-demand resource allocation and interval-based pricing mechanisms. However, it only focused on the scheduling problem for a single workflow but did not well discuss the scheduling problem for multiple workflows. Based on the Pareto theory, Durillo et al. [16] proposed a Multi-Objective Heterogeneous Earliest Finish Time (MOHEFT) algorithm in cloud environments, which optimized workflow execution time and resource utilization. Moreover, Wang et al. [22] designed a Cloud scientific wOrkflow SchedUling algoRithm based on attack-defensE game model (CLOSURE), which reduced the attacker’s benefits and the time costs of the algorithm. Different from these two work, we consider optimizing resource utilization and workflow execution costs with deadline constraints in MCEs. Arabnejad et al. [23] designed a heuristic Budget Deadline Aware Scheduling (BDAS) algorithm targeted for a single workflow with budget and deadline constraints in clouds, which made a balance between budget and deadline constraints and thus improved the success rate of workflow scheduling while optimizing the execution costs. However, this work only considered the scheduling problem for a single workflow. In our previous work [18], we adopted the PCP theory to handle the scheduling problem for a single SW with deadline constraints in MCEs, which optimized the execution costs by compressing data communication. Moreover, we developed an Adaptive Discrete Particle Swarm Optimization with Genetic Algorithm (ADPSOGA) in [24] for scheduling a single SW with deadline constraints in MCEs, which can reduce the execution costs while meeting deadline constraints. However, they only focused on a single workflow, the scheduling problem for multiple SWs was not well considered.

In response to multiple SWs, Malawski et al. [19] designed a dynamic scheduling algorithm, which took into account the uncertainty of task execution time and the startup delay of instances, to guarantee the completion rate of scheduling SWs under budget and deadline constraints. However, this work only relied on one instance type but not multiple ones in MCEs. Lorido-Botran et al. [25] and Kang et al. [26] improved resource utilization and reduced execution costs based on the principles of instance scheduling scaling and rule scaling, respectively, which adaptively turned on or off instances while meeting the performance requirements of SWs. To some extent, these two works enlighten the instance allocation and consolidation proposed in our work, but they did not consider deadline constraints. Mao and Humphrey [27] proposed an adaptive resource scaling
method that can reduce the total cost of executing instances. Moreover, Wangsom et al. [28] developed a new scheduling framework to optimize network utilization and energy consumption in a cloud data center. However, these two work only targeted at a single cloud environment but did not consider the problems of instance allocation and task scheduling in MCEs. Based on the equal-weight task division in multiple SWs, we designed an online fault-tolerant scheduling strategy in our previous work [21], which can guarantee the high success rate of completing multiple SWs in hybrid cloud environments. By contrast, the objective of this work is to enhance the utilization of instance resources and reduce the total costs of executing multiple SWs in MCEs.

III. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we introduce the proposed online workflow scheduling model in detail. As shown in Figure 1, the proposed model consists of multiple scientific workflows (SWs), a multi-cloud environment (MCE), and a cloud broker who serves as the online workflow scheduler. In the proposed model, multiple SWs with deadline constraints are scheduled by the proposed OWS-A2C, where the SW tasks are distributed to the appropriate execution instances while the idle ones are consolidated adaptively. Thus, not only the utilization of instance resources is improved but also the total execution costs are reduced. Meanwhile, the proposed model ensures that each SW can be completed before their sub-deadlines.

We assume that an SW $W_i$ is described by using a directed acyclic graph (DAG), denoted by $G_i( \text{Vertex}_i, \text{Edge}_i )$, where $\text{Vertex}_i = \{ t_{i1}, t_{i2}, \ldots, t_{im} \}$ and $\text{Edge}_i = \{ e_{i12}, e_{i13}, \ldots, e_{ijk} \}$ are the sets of task nodes and dependencies, respectively. More specifically, $e_{ijk} = (t_{ij}, t_{ik})$ indicates that there is a dependency between the tasks $t_{ij}$ and $t_{ik}$, where $t_{ik}$ is the child task of $t_{ij}$ and $t_{ij}$ is the parent task of $t_{ik}$. In this work, we focus on the impact of adaptive resource allocation and consolidation on SW scheduling, and thus the data transmission between different tasks is neglectable while the storage capacity is assumed to be unlimited [29], [30]. During the scheduling process, a child task can only be executed after all its parent tasks have been completed. Moreover, each SW has its deadline constraint, denoted by $D(t_{w_i})$, which represents the expected completion time of an SW.

In an MCE, there are multiple cloud service providers (CSPs), denoted by $P = \{ p, q, r, \ldots \}$. For a CSP $p$, it can provide different types of instances, denoted by $S_p = \{ s_{p1}, s_{p2}, \ldots, s_{pm} \}$. We define the execution time of the task $t_{ij}$ on the instance $s_{pk}$ as $T_{exe}(t_{ij}, s_{pk})$, and it is assumed to be known. Meanwhile, the cost-performance might be different when tasks are executed on various types of instances. Moreover, we assume that all instances are equipped with single-core and perform serial processing, and thus only one task can be executed at a time. Besides, a pricing unit time (denoted by $\lambda_p$) is specifically set by the CSP $p$ for providing services, and the instance $s_{pk}$ is set a corresponding price in unit time (denoted by $c_{pk}$).

As the objective of our work is to optimize the computational costs of execution instances, other aspects of costs such as storage, retrieval, analysis, and task conversion are not taken into account [18]. We define the scheduling plan as $S = (R_e, M_{ap}, T_{total}, C_{total})$, where $R_e = \{ v_{m1}, v_{m2}, \ldots, v_{mr} \}$ is the set of activated instances, $M_{ap} = \{ (t_{ij}, v_{mk}) | t_{ij} \in \text{Vertex}_i, v_{mk} \in R_e \}$ is the mapping relationship between tasks and execution instances, $T_{total}$ is the completion time of SWs, and $C_{total}$ is the total execution costs. Moreover, the moments of turning on and off for each execution instance are denoted by $T_{on}(v_{mi})$ and $T_{off}(v_{mj})$, respectively. When the task $t_{ij}$ is completed, its actual end and start moments are recorded, denoted by $AET(t_{ij})$ and $AST(t_{ij})$, respectively.
Therefore, the total execution costs are defined as
\[
C_{\text{total}} = \sum_{i=1}^{\lceil Tle(vm_i) - Tls(vm_i) \rceil} e_s(vm_i), \quad (1)
\]
where \(s(vm_i)\) is the instance type, \(e_s(vm_i)\) is the corresponding unit-time price, \(p(vm_i)\) is the CSP who provides the instance, and \(\lambda(vm_i)\) is the pricing unit time of the CSP.

Since many execution instances might be activated for meeting the service requirements of multiple SWs, our optimization objective is to improve the average resource utilization of execution instances. Based on the above definitions, we formulate the online scheduling problem for multiple SWs with deadline constraints in MCEs as

\[
\begin{align*}
\text{Maximize} & \quad U_{\text{instance}} \\
\text{Minimize} & \quad C_{\text{total}} \\
\text{Subject to} & \quad \forall w_i, \max\{\text{ATE}(t_{ij})\} \leq D(w_i), \quad (2)
\end{align*}
\]

where \(U_{\text{instance}}\) indicates the average resource utilization of execution instances, and our optimization objective is to maximize \(U_{\text{instance}}\) and minimize \(C_{\text{total}}\) while meeting deadline constraints.

**IV. DESIGN OF THE OWS-A2C**

In this section, we present the proposed Online Workflow Scheduling algorithm based on Adaptive resource Allocation and Consolidation (OWS-A2C). The proposed method can be used to schedule multiple SWs in real-time and effectively allocate and consolidate instance resources based on the system status of MCEs. In MCEs, pricing mechanisms rely on unit intervals without considering the actual execution time of instances. Therefore, it is necessary to consolidate instances that are not fully utilized. First of all, we reassign task deadlines according to the execution performance of instances, which can improve resource utilization from a local perspective when executing an SW. Next, the instances are allocated and consolidated based on the performance requirements of multiple SWs, which can enhance resource utilization and reduce the total costs of executing SWs from a global perspective. Finally, the SW tasks are dynamically scheduled to execution instances by following the EDF discipline while ensuring that all tasks can be completed before their sub-deadlines. More details are given in the following sub-sections.

**A. DEADLINE REASSIGNMENT**

For an SW, it has its own deadline constraint. Before scheduling, the tasks in an SW need to be divided so that they can be scheduled independently (without dependencies). Next, the deadline of the SW is reassigned to the tasks, which forms their sub-deadlines. If all tasks in an SW are completed before their sub-deadlines, the SW would be completed under its deadline constraint.

The key steps of the deadline reassignment are shown in Algorithm 1.

**Algorithm 1 Deadline Reassignment**

1: **Procedure** ReassignDiil(Gi(Vertexi, Edgei), D(wi))
2: Confirm the valid instance types in an MCE.
3: for each \(t_{ij}\) in \(w_i\) do
4: Schedule \(t_{ij}\) to \(vm_{pkr}\) with the highest cost-performance.
5: end for
6: Form a hypothetical scheduling plan \(Map\).
7: Call Pa2Se(Gi(Vertexi, Edgei), D(wi), Map).
8: while true do
9: if makespan(\(Map\)) \leq D(wi) then
10: return \(Map\).
11: else
12: for each \(t_{ij}\) in \(w_i\) do
13: \(Map_{ij} = Map - (t_{ij} \rightarrow vm_{pkr}) + (t_{ij} \rightarrow nextFasterVM)\).
14: \(rank_{ij} = \frac{\text{makespan}(\text{Map})-\text{makespan}(\text{Map}_{ij})}{\text{cost}(\text{Map})-\text{cost}(\text{Map}_{ij})}\).
15: end for
16: index = subscript(max(rank_{ij})).
17: \(Map = Map_{\text{index}}\).
18: end if
19: end while
20: **End Procedure**

First of all, the valid instance types in an MCE need to be confirmed, and the tasks in an SW are scheduled to the corresponding instances with the highest cost-performance, and thus a hypothetical scheduling plan is formed (Lines 2~6), denoted by \(Map\). This plan only represents the theoretical calculation and serves as a reference for subsequent actual scheduling. Moreover, it should be noted that one instance may need to execute tasks from multiple different SWs simultaneously in the multi-workflow scheduling problem. Next, parallel tasks are converted to serial ones (Line 7). This is because there might be a large amount of remaining execution time when multiple parallel small tasks occupy execution instances alone [31]. If the makespan of \(Map\) does not exceed the deadline of the corresponding SW, \(Map\) will be output (Lines 9~10). Otherwise, \(Map\) will be updated iteratively (scheduling tasks to execution instances with faster processing speed). Finally, among the recorded feasible plans (meeting deadline constraints), the plan with the highest cost-performance rank (denoted by \(Map_{\text{index}}\)) will be selected and output (Lines 12~17). The rank is defined as

\[
rank = \frac{\text{makespan}(\text{Map}) - \text{makespan}(\text{Map}_{ij})}{\text{cost}(\text{Map}) - \text{cost}(\text{Map}_{ij})}, \quad (3)
\]

where the functions \(\text{makespan()}\) and \(\text{cost()}\) are used to calculate the makespan and execution costs of a scheduling plan, respectively.

Algorithm 2 shows the conversion from parallel to serial tasks in detail, which can be used to improve the resource
Algorithm 2 Conversion From Parallel to Serial Tasks

1: **Procedure** P2S(e(V, E), D, Map)
2:  for each \( t_{ij} \) and \( t_{ik} \) in \( w_i \)
3:     if \( t_{ij} \) and \( t_{ik} \) have the same parent and child nodes
4:         Convert \( t_{ij} \) and \( t_{ik} \) to serial tasks and schedule them to instances with the fastest processing speed.
5:     if \( Map \) cannot satisfy deadline constraint then
6:         Rollback to the previous status Map'.
7:     end if
8:  end if
9: end for
10: End Procedure

B. INSTANCE ALLOCATION AND CONSOLIDATION

1) INSTANCE ALLOCATION

After the deadline reassignment, each task has a corresponding execution interval, which is defined as

\[
\text{Interval}_{ij}(T_{start}, T_{end}) = T_{end} - T_{start} \quad (4)
\]

where \( T_{start} \) and \( T_{end} \) represent the start and end time of the task execution, respectively.

Moreover, we define an execution vector for the SW \( w_i \) corresponding to a certain instance type, denoted by \( EV(w_i, s_{pk}) = [ev(t_{i1, s_{pk}}), ev(t_{i2, s_{pk}}), \ldots, ev(t_{in, s_{pk}})] \), where \( ev(t_{ij, s_{pk}}) \) indicates the number of instances of the type \( s_{pk} \) required to complete the task \( t_{ij} \), which is defined as

\[
ev(t_{ij, s_{pk}}) = \frac{T_{exe}(t_{ij, s_{pk}})}{\text{Interval}_{ij}(T_{start}, T_{end})}. \quad (5)
\]

When \( ev(t_{ij, s_{pk}}) > 1 \), the execution time exceeds the corresponding execution interval, and thus the task \( t_{ij} \) cannot be completed within its sub-deadline by using the current instance type. For example, after deadline reassignment, the execution interval of the task \( t_{ij} \) is \( Interval_{ij}(5:00, 6:00) \). We assume that the execution time of this task on the instance \( v_{m_{pk}} \) is 30 minutes, and thus the corresponding value of \( ev(t_{ij, s_{pk}}) \) would be \( \frac{1}{2} \). Since this value does not exceed 1, the task \( t_{ij} \) can be scheduled to the instance \( v_{m_{pk}} \) and completed within its execution interval.

Besides, the execution vectors for the SW \( w_i \) corresponding to all instance types can be expressed by using the matrix \( S_{EV} \) as

\[
S_{EV} = \begin{bmatrix}
    ev(t_{i1, s_{pk}}), ev(t_{i2, s_{pk}}), \ldots, ev(t_{in, s_{pk}}) \\
    ev(t_{i1, s_{qk}}), ev(t_{i2, s_{qk}}), \ldots, ev(t_{in, s_{qk}}) \\
    \vdots \\
    ev(t_{i1, s_{rk}}), ev(t_{i2, s_{rk}}), \ldots, ev(t_{in, s_{rk}})
\end{bmatrix}. \quad (6)
\]

By adding the row vectors of \( S_{EV} \), the number of execution instances of different types required to complete the SW \( w_i \) before its deadline \( D(w_i) \) can be obtained, denoted by \( Np = \{N_{pk}, N_{qk}, N_{rk}, \ldots\} \), where \( N_{pk} \) is the number of execution instances of the type \( s_{pk} \). During the scheduling process, if the allocated number of execution instances is always greater than or equal to the required ones, all SW tasks would be completed before their sub-deadlines.

2) INSTANCE CONSOLIDATION

An expected scheduling plan is able to schedule tasks to the execution instances with the highest cost-performance, while the instances can achieve high resource utilization. However, due to the different execution time of tasks, the resource utilization of some execution instances may be low in the scheduling process. To address this problem, it is necessary to perform instance consolidation and migrate some tasks to the instances that are not with the highest cost-performance, which can help improve resource utilization and reduce execution costs. As shown in Figure 3, for example, the tasks \( t_{1j} \), utilization of execution instances. First of all, if the parallel tasks have the same parent and child nodes and their execution time does not exceed half of their execution instances’ pricing unit time, they will be converted to serial tasks and scheduled to the instances with the fastest processing speed (Lines 3–4). During this process, the execution time of a scheduling plan might exceed the deadline. When this happens, the rollback operation will be taken and the scheduling status will return to the previous one that satisfies the deadline constraint (Lines 5–6).

Taking Figure 2 as an example, the SW occupies 5 execution instances, where the tasks \( t_3, t_4, t_5, \) and \( t_6 \) have the same parent node \( t_1 \) and child node \( t_7 \), and each of these parallel tasks occupies one execution instance, respectively. By following Algorithm 2, the tasks \( t_3, t_4, t_5, \) and \( t_6 \) are converted to serial tasks and scheduled to \( v_{m_3} \), where \( v_{m_3} \) is assumed to offer the fastest processing speed. Thus, the costs of two execution instances (i.e. \( v_{m_4} \) and \( v_{m_5} \)) can be saved.

![FIGURE 2. An example of the conversion from parallel to serial tasks.](image-url)
and \( t_2 \) are scheduled to the instances \( vm_{pk1} \) and \( vm_{pj1} \), respectively. However, these two tasks only occupy a small part of the pricing unit interval while there are no other tasks to be executed in this interval. Therefore, they are consolidated and scheduled to the instance \( vm_{pk1} \). Although the instance \( vm_{pk1} \) may not offer the highest cost-performance to the task \( t_2 \), the execution costs of the instance \( vm_{pj1} \) in a unit time can be saved by instance consolidation. During the process, each task is guaranteed to be completed before their deadlines.

The key steps of the instance consolidation are shown in Algorithm 3. First of all, the algorithm checks different types of instance resources (denoted by \( Re_{pk} \)) activated in the current MCE and the number of different types of instances (denoted by \( Re_{pk} \)) (Line 2). If the required number of execution instances of the type \( s_{pk} \) is greater than the currently activated ones, the algorithm will search for other instance types with remaining resources and schedule the uncompleted tasks to these instances (Lines 4~10), where \( t_{top in s_{pk}} \) represents the task that is closest to its sub-deadline. Finally, the algorithm keeps running until the number of activated instances exceeds the required ones (Lines 11~12).

Algorithm 3 Instance Consolidation

1: Procedure ConsolidateIns\( (Np, Re) \)
2: Check the active instance types \( Re \) and the number of instances \( Re_{pk} \).
3: for each \( s_{pk} \) do
4: if \( N_{pk} > Re_{pk} \) then
5: for each \( s_{qk} \) do
6: if \( N_{qk} + ev(t_{top in s_{pk}}, s_{qk}) \leq Re_{qk} \) then
7: \( N_{pk} = N_{pk} - ev(t_{top in s_{pk}}, s_{pk}) \).
8: \( N_{qk} = N_{qk} + ev(t_{top in s_{pk}}, s_{pk}) \).
9: Schedule \( t_{top in s_{pk}} \) to an instance of \( s_{qk} \).
10: end if
11: if \( N_{pk} \leq Re_{pk} \) then
12: break.
13: end if
14: end if
15: end if
16: end for
17: end Procedure

3) ONLINE SCHEDULING FOR MULTIPLE SWs

Through the instance allocation and consolidation, the required number of different types of execution instances can be determined. Furthermore, based on the earliest-deadline-first (EDF) discipline [32], the online scheduling is performed for the tasks whose deadlines have been reassigned. For a certain type of execution instances, all the tasks on the corresponding instances are sorted by their sub-deadlines. When an instance is available, the tasks will be scheduled to this instance by following the EDF discipline.

More specifically, the flow of the proposed OWS-A2C is shown in Figure 4, where the detailed steps are listed as follows.

**Step 1:** Monitor and collect the status information such as valid instance types, activated execution instances, and corresponding task execution progress in an MCE.

**Step 2:** According to Algorithm 1, reallocate the task deadlines in SWs and calculate their corresponding execution intervals. To reduce resource waste, Algorithm 2 is used to convert parallel tasks to serial ones.

**Step 3:** Update the execution vectors corresponding to different instance types for each task, and generate the execution matrix \( S_{EV} \) for each SW.

**Step 4:** Check the execution status and available resources of the activated execution instances, and perform instance consolidation by using Algorithm 3.

**Step 5:** Determine whether the existing instance resources are sufficient. If the current instance resources are insufficient, activate the required number of execution instances and skip to Step 2. If the current instance resources are sufficient, further determine whether the resource waste happens. If the current instance resources are surplus, shut down idle execution instances. Otherwise, skip to Step 6.

**Step 6:** Based on the current status of SW tasks and execution instances, schedule the tasks by following the EDF principle.

V. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the proposed OWS-A2C for SW scheduling and make comparisons with three baseline scheduling methods.
A. SETTINGS AND DATASETS

The simulation environment is established on Windows 7 64-bit with Intel® Core™ i7 CPU @2.30 GHz and RAM 8.00 GB DDR4. Specifically, we implement the multi-cloud simulation environments and the proposed scheduling method for multiple SWs based on Python 3.6, where NumPy is used to provide massive mathematical function libraries for array and matrix operations. Moreover, five types of SWs are used in our simulations including Montage, CyberShake, Epigenomics, LIGO, and SIPHT [33], where each one has its unique structure. For example, there are many parallel tasks in LIGO and SIPHT without obvious task dependency. By contrast, there are many serial tasks in Epigenomics with many task dependencies. For each SW type, a medium-size SW with around 100 tasks is chosen.

Next, three representative load modes are selected for each SW type [34], including the steady-load, growing-load, and switching-load modes. As shown in Figure 5, we simulate the arrival pattern and number of multiple SWs within 72 hours, where the time interval of SWs’ arrivals is 5 minutes. In the steady-load mode, the number of arriving SWs is stable with little fluctuations. In the growing-load mode, the number of arriving SWs grows rapidly. In the switching-load mode, the number of arriving SWs shows a strong time correlation.

Moreover, we assume that there are three CSPs (i.e., C1, C2, and C3) in an MCE, where each CSP offers 8 instance types with the corresponding processing speed and execution cost per unit time. Among the types provided by C1(C2/C3), the fastest processing speed of a type is approximately 5(8/10) times the slowest one. Correspondingly, the execution cost increases by the same multiple [18]. Specifically, the execution cost per unit time of an instance type with the slowest processing speed in each CPS is set to 2 USD/hour, and the pricing unit time is set to 1 hour [35]. Furthermore, the task execution time of the instance with the slowest processing speed is the same as that generated by the workflow generator proposed in [36], which facilitates the evaluation of scheduling systems and algorithms for different SW sizes and parameterizes the information collected from the actual executions of SWs to generate synthetic SWs that can resemble those used by real-world scientific applications. In addition, we assume that about one-third of tasks in an SW can be executed on the instances with the corresponding highest cost-performance [23].

Finally, we define five different deadlines for each SW as

\[ D_k(w_i) = r_k \cdot \min(w_i) \]

where \( k = \{1, 2, \ldots, 5\} \), and \( \min(w_i) \) is the time required for completing the SW \( w_i \) by using the Heterogeneous Earliest-Finish-Time (HEFT) algorithm [37], and the value of \( r_k \) is sequentially taken from the set \( R = \{1.2, 1.5, 3, 5, 8\} \).

To validate the effectiveness of the proposed OWS-A2C, we first modify three scheduling algorithms proposed in the related work so that they can adapt to the current scenario. Next, we regard them as baseline scheduling methods and conduct comparative experiments. The detailed descriptions are given as follows.

- **GAINM.** By extending the GAIN algorithm [14], the GAIN with Modification GAINM (algorithm can better adapt to the cost optimization problem of scheduling multiple SWs with deadline constraints in MCEs. Firstly, the GAINM select the instance type with the lowest execution cost to schedule the tasks of a single SW. Next, the scheduling plan is continuously updated according to Equation (3) until the execution time satisfies the deadline constraints.

- **PHGS.** By referring to our previous work [21], the Partition Hierarchically and Greedy Scheduling (PHGS) algorithm first estimates the earliest start time and sub-deadlines of unscheduled tasks based on the equal-weight task division. Next, the tasks are scheduled to the execution instances that satisfy the sub-deadline constraints and consume the lowest execution cost by the greedy algorithm.

- **PHA2CI.** The deadline reassignment relies on SW structures and task weights by using the equal-weight task division [21], but it does not consider instance types. Therefore, the Partition Hierarchically based on the Adaptive Allocation and Consolidation for Instances (PHA2CI) algorithm is designed to better evaluate the
impact of deadline reassignment on scheduling results, because it performs instance allocation and consolidation during the scheduling process.

B. EXPERIMENTAL RESULTS

As load modes and the arriving number of multiple SWs might be various, we use an average execution cost (denoted by $\text{Avg}_{\text{Nec}}(W)$) and average utilization of execution instances (denoted by $\text{Avg}_{\text{Uti}}(\text{VM})$) as the performance indexes for evaluating different scheduling methods, which are defined as

$$\text{Avg}_{\text{Nec}}(W) = \frac{C_{\text{total}}(W)}{N(W) \cdot \min_{w_i \in W} \{CC(w_i)\}}, \quad (8)$$

$$\text{Avg}_{\text{Uti}}(\text{VM}) = \frac{\sum_{i=1}^{M} \text{Uti}(vm_i)}{M}, \quad (9)$$

where $C_{\text{total}}(W)$ represents the total execution costs and $N(W)$ is the number of arriving multiple SWs. $\min_{w_i \in W} \{CC(w_i)\}$ indicates the lowest cost of scheduling each SW to the corresponding instances by using the greedy algorithm in a single cloud environment, which does not consider deadline constraints. Moreover, $M$ and $\text{Uti}(vm_i)$ represent the number of activated execution instances and the resource utilization of each instance during the scheduling process, respectively.

Figures 6, 7, and 8 show the average execution cost and utilization of execution instances for scheduling three types of SWs (i.e. CyberShake, Epigenomics, and LIGO) under three load modes (i.e. steady-load, growing-load, and switching-load modes), respectively. In general, these scheduling methods achieve their corresponding best performance in the growing-load mode, followed by the steady-load and switching-load modes. This is because the number of arriving SWs in the growing-load mode is constantly increasing, and thus there are fewer idle instances, which leads to higher resource utilization and lower average execution cost. By contrast, numerous execution instances need to be activated during the peak period under the switching-load mode, and thus many idle instances might occur after this period, which will result in lower resource utilization and higher average execution cost.

Compared to other scheduling methods, the proposed OWS-A2C shows the best performance, while the PHGS performs worst in most cases. This is because the PHGS performs the deadline reassignment only based on the task loads, thus it is hard to find the best execution instance to satisfy the reassigned sub-deadlines. Meanwhile, the PHGS uses the greedy algorithm to select scheduling plans, which may save some execution costs when dealing with a single SW. However, when it comes to multiple SWs, this method will cause higher execution costs. By contrast, the PHA2CI performs the instance consolidation after the deadline reassignment, so it outperforms the PHGS in most cases. Moreover, the GAINM chooses the instance with the highest cost-performance to schedule tasks, and thus it is more suitable for scheduling multiple SWs. Because execution instances receive more tasks as the number of SWs rises, and thus their utilization will increase and execution costs will decrease. But in some cases of the LIGO, the performance of the GAINM may be slightly inferior to the PHGS, as shown in Figures 8(a) and (b). This is because there are many parallel tasks in the LIGO, which might influence the optimization effect on execution costs when the deadline is tight (e.g. D1).

Moreover, as shown in Figures 7(b) and (c), when the deadline is tight (e.g. D1), the performance gap between
different methods is small. This is because all these methods tend to schedule tasks to the instance with the fastest processing speed when they face strict deadlines. Correspondingly, the average resource utilization of execution instances is not high in this case. Since there are many serial tasks in the Epigenomics, the optimization space for execution costs might thus be limited. With the relaxation of deadline constraints, the performance of the OWS-A2C becomes more excellent. This is because the proposed method comprehensively considers the cost-performance, resource utilization, and execution costs of execution instances in the process of scheduling optimization. By contrast, the PHGS does not take the above important factors into account, so its performance is severely degraded when deadline constraints become loose.

As for the other two types of SWs including Montage and SIPHT, their corresponding scheduling performances

FIGURE 7. Performance comparisons of scheduling Epigenomics under various load modes among different methods.

FIGURE 8. Performance comparisons of scheduling LIGO under various load modes among different methods.

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achieved by using different scheduling methods under various load modes are similar to the cases of the CyberShake and Epigenomics, as shown in Figures 6 and 7, respectively. Therefore, the descriptions will not be repeated.

VI. CONCLUSION AND FUTURE WORK
The complex task dependencies and various resource cost-performance impose great challenges on scheduling multiple SWs with deadline constraints in MCEs. To address these challenges, we propose an OWS-A2C method to perform the online SW scheduling with adaptive resource allocation and consolidation. The extensive simulation experiments demonstrate the effectiveness of the proposed method in achieving adaptive and efficient SW scheduling in MCEs. More specifically, the OWS-A2C outperforms three baseline scheduling methods, including GAINM, PHGS, and PHA2CI, in terms of average execution cost and resource utilization. In future work, we will consider the interference of fluctuations of instances’ execution performance on scheduling results and further improve the robustness of the proposed algorithm. Moreover, we will take the data transmission between tasks into account for extending the application scenarios of the algorithm and verify it in real-world environments.

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