Energy-efficient workflow scheduling based on workflow structures under deadline and budget constraints in the cloud

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Abstract—The utilization of cloud environments to deploy scientific workflow applications is an emerging trend in scientific community. In this area, the main issue is the scheduling of workflows, which is known as an NP-complete problem. Apart from respecting user-defined deadline and budget, energy consumption is a major concern for cloud providers in implementing the scheduling strategy. The types and the number of virtual machines (VMs) used are determinant to handle those issues, and their determination is highly influenced by the structure of the workflow. In this paper, we propose two workflow scheduling algorithms that take advantage of the structural properties of the workflows. The first algorithm is called Structure-based Multi-objective Workflow Scheduling with an Optimal instance type (SMWOS). It introduces a new approach to determine the optimal instance type along with the optimal number of VMs to be provisioned. We also consider the use of heterogeneous VMs in the Structure-based Multi-objective Workflow Scheduling with Heterogeneous instance types (SMWSH), to highlight the algorithm’s strength within the heterogeneous environment. The simulation results show that our proposal produces better energy-efficiency in 80% of workflow/workload scenarios, and save more than 50% overall energy compared to a recent state-of-the-art algorithm.

Index Terms—Cloud computing, Workflow scheduling, Energy minimization, Budget, Deadline

I. INTRODUCTION

Energy consumption has been a major issue in cloud environments. That high energy consumption has been traced from several sources, among which the servers are the main power consumers $^1$$^2$$^3$. In early 2010, researchers reported that under-utilization of cloud resources $^4$$^5$$^6$ contributes to the high energy consumption in cloud data centers, which is caused by the inefficient scheduling allocation of servers resources $^7$$^8$$^9$. Many works have been carried out to improve the energy-efficiency of clouds, from idle servers switching off $^2$, VMs/workload consolidation $^7$$^8$$^9$, to the Dynamic Voltage and Frequency Scaling (DFVS) $^10$$^11$$^12$$^13$ techniques.

As commercial clouds gradually emerge as promising environments for the execution of scientific workflow applications on many domains such as biology, physics, medicine, and astronomy $^14$$^15$$^16$, it creates more complex challenges in term of workflow scheduling. A workflow may contain hundreds or thousands of interdependent tasks which are executed under a permanent dependency constraint where a task can only start its execution if the executions of its parents are completed. That means, allocated cloud resources can hardly be fully utilized as they might be inevitable gaps between tasks execution. This challenge brings together the complexity of clouds management along with the workflow structures complexity. The level of difficulty of cloud workflow scheduling becomes very high, especially if we consider multiple user defined Quality of Service (QoS) parameters (e.g., deadline, cost). It is very important to correctly determine the types and the number of cloud resources $^17$$^18$ to avoid the energy wastage and the violation of Service Level Agreement (SLA). No matter the types of resources being used, it is highly inefficient for the cloud providers to provision VMs in a larger amount than the largest number of tasks of the workflow’s width for its execution $^17$. Therefore, It is crucial to determine the optimal number and the types of VMs to use during the execution of a workflow, to avoid resource wastage and to ensure the SLA fulfilment as well as providing a reasonable profit for the cloud providers. A good prediction of number and type of resources for the execution of a workflow is a good asset for the designing the energy-efficient techniques.

To the best of our knowledge, only few works $^17$ focused on determining suitable instance types set or a number of VMs instances in advance with an analytical approach. Some solutions use a naive determination approach in which it is at the end that one realize which types and the number of VMs have been used, leading in more cases to a wastage (too many provisioned VMs that are less utilized). Others are time consuming determination approaches, like greedy determination $^19$ and paths-based clustering determination $^10$$^20$. The paths-based clustering approach is better than the greedy one, however, its complexity and effectiveness are compromised if the workflow graph is strongly connected. Moreover, most of the solutions in the literature are effective only for a few types of workflow, while the types and structures of workflow are very complex and varied $^21$. This is not conform with the recommendation $^21$$^18$ of designing scheduling strategies that are effective no matter the type of workflow.

We advocate that homogeneity can produce better results if the good instance is chosen for the workflow execution. We further advocate that the provisioning of a correct number of suitable VMs can help not only to produce better results, but also to improve the VM utilization and further reduce the...
energy consumption.

In this paper, we introduced a new technique based on structural properties of workflows and user-defined budget and deadline, to determine an "optimal instance type" along with the "optimal number" of VMs for adequate provisioning. In our strategy, all of the VMs used are of the same type (i.e., optimal instance type), and their number is limited by the "optimal number". Two scheduling algorithms are proposed, Structure-based Multi-objective Workflow Scheduling with an Optimal instance type (SMWSO), and Structure-based Multi-objective Workflow Scheduling with Heterogeneous instance types (SMWSH). Both algorithms aim at minimizing energy consumption, makespan, and execution cost under user-defined deadline and budget. The effectiveness of our algorithms have been proved through comparative simulations against Reliability and Energy Efficient Workflow scheduling (REEWS), a recent state-of-the-art algorithm [10]. The choice of REEWS is because it used a clustering technique to determine the number of VMs to be used and the DVFS to minimize energy consumption.

The remaining sections of the paper are organized as follows. Section 2 presents related work. In Section 3 we define the workflow scheduling problem. Section 4 describes the proposed scheduling heuristics, while Section 5 presents the experimental setup and analyses the results of the simulation experiments. Section 6 summarizes and concludes the paper.

II. RELATED WORK

One of the most widely used techniques in heuristic workflow scheduling is the list-based scheduling, represented by the Heterogeneous Earliest Finish Time (HEFT) proposed by Topcuoglu et al. [22]. HEFT aims to minimize the makespan of workflow execution in heterogeneous environments. It sorts the tasks of the workflow into a scheduling list and then assigns each task to the resource which can finish it the earliest. The determination of the finish time takes into account the already mapped tasks to each VM and find (with insertion base) the first time slot that can accommodate the task according to the precedence constraints in the workflow.

In [23], the Cost-Time Trade-off Workflow Scheduling (CTTWS) algorithm has been proposed, which aims at minimizing execution cost and execution time under user-defined budget and deadline. The CTTWS algorithm uses a trade-off function between cost and time, combined with the Implicit Requested Instance Types Range (IRITR) which is a technique aiming at determining a suitable (sub-)set of VMs to be used in order to avoid overbidding and underbidding. CTTWS has proved to be better to meeting users’ deadlines and budgets up to 38.4% according to the variety of available instance types compared to the state-of-the-art. However, CTTWS rely on static VM provisioning, and failed to produce good results for SIPHT workflow due to its structure. A dynamic version of CTTWS is proposed in [17], denoted Cost-time trade-off workflow scheduling with dynamic provisioning (CTTWSDP). The CTTWSDP algorithm introduces a structure inspired dynamic VM selection and limitation. It improves the IRITR and limits the number of VMs to provision to the average width of the workflow. Through comparative simulation using five wide spread workflows, each with five different size of tasks, CTTWSDP has proved to be more effective than four state-of-the-art algorithms. Moreover, CTTWSDP is significantly effective no matter the type and the workload of workflow.

Among the algorithms proposing energy-efficient techniques we include Kimura et al. [24] that proposed a slacking algorithm that uses the non-critical path to extends the task execution time by reclaiming slack time to save energy. Huang et al. [25] present an enhanced Energy-Efficient Scheduling (EEWS) algorithm which reduces energy consumption while meeting the performance-based requirements. Then, Durillo et al. [26] proposed an extended version of the HEFT algorithm denoted multi-objective heterogeneous earliest finish time (MOHEFT) aiming at providing suitable trade-offs between makespan and energy consumption.

Furthermore, Huang et al. [25] also proposed two algorithms extending the HEFT algorithm by introducing the energy awareness, called the Enhancing Heterogeneous Earliest Finish Time (EHEFT) and the Enhancing Critical Path on a Processor (ECPOP), and addressed the time and energy-efficient workflow scheduling. Tang et al. [12] introduce the DVFS enabled Efficient energy Workflow Task Scheduling (DEWTS) algorithm to obtain more energy reduction. However, the last two algorithms reserve a set of VM instances for the whole makespan.

Then, Li et al. [11] proposed cost and energy-aware scheduling (CEAS) algorithm to minimize the execution cost of workflow and reduce the energy consumption while meeting the deadline constraint in the cloud environment. CEAS first uses a VM selection algorithm that applies the concept of cost-utility to map tasks to their optimal virtual machine (VM) types by the sub-makespan constraint. Afterwards, it employs two tasks merging methods to reduce execution cost and energy consumption. In order to reuse the idle VM instances which have been leased, it further proposed a VM reuse policy. And finally, it utilized a scheme of slack time reclamation to save energy of leased VM instances.

More recently, Ritu Garg et al. [10] proposed the Reliability and Energy Efficient Workflow scheduling (REEWS) algorithm. The aim of their proposal is to minimize the energy consumption and maximize the reliability of the workflow execution in the respect of the user-specified QoS/deadline constraint. The REEWS algorithm consists of four main steps: the prioritization of the tasks; the tasks clustering; (user-defined) deadline distribution among the workflow tasks and the mapping of cluster tasks to processors at suitable voltage/frequency levels in order to maximize the overall reliability of the system and minimize of energy consumption.

Singh et al. [27] proposed a meta-heuristic called energy efficient workflow scheduling (EEWS) algorithm, aiming at minimize makespan and energy consumption. EEWS is inspired from hybrid chemical reaction optimization (HCRO) algorithm, and adds a new operator called on-wall pseudo-effective collision to exploit the benefits of swap mutation, and
consider dynamic voltage scaling (DVS) along with a novel proposed measure to calculate the amount of energy that can be conserved.

Neha Garg et al. [7] proposed the energy and resource efficient workflow scheduling (ERES) algorithm, which aims at minimizing energy consumption, maximizing resource utilization, and minimizing workflow makespan. The ERES algorithm uses VM migration to deploy/un-deploy the VMs based on the workflow task’s requirements and a double threshold policy to perceive the server’s status (overloaded/underloaded or normal). ERES also makes use of the DVFS technique.

### III. MODELLING OF THE MULTI-OBJECTIVE WORKFLOW SCHEDULING PROBLEM

In this section, we present the cloud resource model, the power and energy models, the workflow model, and the problem formulation. The meanings of the parameters found throughout this paper are summarized in Table I.

#### A. Cloud computing model

The cloud data center model is similar to the one offered by Amazon EC2 [28]. We assume that the data center is equipped with a set of $K$ types of heterogeneous VM instances, denoted by VMIT= \{vmit1, vmit2, ..., vmitK\}, having various processing costs, performances and configurations. Each instance type $\text{vmit}_k$ is defined by its computing performance $p_k$ in millions instructions per second (MIPS), its processing cost per billing period $c_k$ and communication bandwidth $b_k$. An instance with a higher computing performance is . For sake of simplicity, we assume that the communication bandwidth between the instances is uniformly distributed, and denoted by $\beta$.

We consider that $P$ VMs ($\text{VMS} = \{\text{vm}_1, \text{vm}_2, ..., \text{vm}_P\}$), each been of an instance type in VMIT, are leased as subscription-based services in a pay-per-use model and are charged per billing period of length $\tau$. A billing period is one hour per VM usage for most IaaS providers; each partial hour consumed being rounded up to a full hour, such that 1 hour and 1 minute (61 min.) will be considered as 2 hours (120 min.) of utilization. As it is often the case [29]. We assume that all the instance types are ordered according to their characteristics (see Eq. (1) and (2)).

\[
\begin{align*}
    p_1 < p_2 < ... < p_k < ... < p_K, \quad \text{(1)} \\
    c_1 < c_2 < ... < c_k < ... < c_K, \quad \text{(2)}
\end{align*}
\]

#### B. Power and Energy models

In terms of energy consumption among system components, processors consume typically the largest portion [9]. Hence, we will focus on energy consumption of processors. A processor consumes energy either idle or while running a task. The power consumed by a processor $p_k$ during its runtime, noted $P^k$, is expressed by equation [3][9][30].

\[
P^k(u_k(t)) = P^k_{idle} + (P^k_{max} - P^k_{idle}) \times u_k(t), \quad \text{(3)}
\]

where $P^k_{idle}$ and $P^k_{max}$ are the power consumed by the processor when idle and at 100% utilization respectively, whereas $u_k(t)$ is the utilization rate of the processor, which is a function of the time. Therefore, the total energy consumption of a processor $p_k$ over a period of time $[t_0, t_1]$ can be defined as an integral of the power consumption function over the same period (see Eq. (4)).

\[
E^k = \int_{t_0}^{t_1} P^k(u_k(t)) dt \quad \text{(4)}
\]

where the overall energy consumption ($E_{total}$) on all the $P$ VMs is simply the sum of all the energy consumption. We also assume that the DVFS is enabled on the system.

#### C. Workflow model

The most commonly used model for scientific application is workflow represented as a Directed Acyclic Graph (DAG). A DAG is a graph $G(WT, E)$ where $WT = \{t_1, t_2, ..., t_n\}$ is the set of the tasks of the workflow (the weight of task $t_i$, in terms of millions of instructions, is denoted by $Z_i$), and $E = \{e_{i,j} = (t_i, t_j)\} 1 \leq i, j \leq n, i \neq j\}$ a set of edges representing the existing data and control dependencies between tasks. Thus $e_{i,j} \in E$ if there is a precedence constraint between $t_i$ and $t_j \in WT$. Such that the execution of $t_j$ can start only after $t_i$ finishes its execution and sends data (of size $s_{ij}$ in Megabytes (MB)) to $t_j$. Task $t_i$ is a parent of $t_j$ and $t_j$ a child of $t_i$. A task is ready to start its execution when all of its parents have been executed and all its required data have been provided. Any task with no parent is an entry task and any task with no

| TABLE I: Parameters Notation |
|-----------------------------|
| **Notation** | **Description** |
| $G$ | workflow DAG |
| $WT$ | Set of tasks of $G$ |
| $t_i$ | $i^{th}$ task of $WT$ |
| levelWidth($l$) | number of tasks in the level $l$ |
| $\delta$ | The user-defined deadline |
| $\delta_i$ | The sub-deadline of the task $t_i$ |
| $B$ | The user-defined budget |
| VMIT | Set of VMs Instances Types |
| vmit$_k$ | The instance type $k$ of VM |
| VMS | Set of leased VMs |
| vm$_p$ | The $p^{th}$ leased VM |
| $p_k$ | The computing performance of vmit$_k$ |
| $\tau$ | The length of the billing period |
| Cost$_G$ | The total cost of executing a workflow |
| minM$_G$ | The minimum possible makespan |
| minCost$_G$ | The minimum possible execution cost |
| $c_k$ | cost per billing period for vmit$_k$ |
| $Z_i$ | the weight of $t_i$ in millions of instructions |
| $s_{t_i,t_j}$ | Size of Data Transfered from $t_i$ to $t_j$ (in MB) |
| $ET(i,k)$ | Execution time of $t_i$ on a vmit$_k$ VM |
| $TT(i,j)$ | Data Transfer time from $t_i$ to $t_j$ |
| $EC(i,k)$ | Execution cost of $t_i$ on a vmit$_k$ VM |
| $EST(t_i)$ | Earliest Start Time of $t_i$ |
| $EFT(t_i)$ | Earliest Finish Time of $t_i$ |
| $AST(t_i)$ | Actual Start Time of $t_i$ |
| $AFT(t_i)$ | Actual Finish Time of $t_i$ |
| $OCCW(t_i)$ | Sum of $TT(i,j)$, $t_j \in \text{Succ}(t_i)$ |
| $outd(t_i)$ | Number of immediate child of $t_i$ |
| $\beta$ | The communication bandwidth |
| $M_G$ | The workflow completion time (makespan) |
| $\text{map}(i)$ | The VM on which $t_i$ is mapped to |
child is an exit task. The set of the parents (resp. children) of the task \( t_j \) is denoted \( \text{pred}(t_i) \) (resp. \( \text{succ}(t_i) \)). The Critical Path (CP) of a DAG is defined as its longest path.

A workflow can have one or more entry tasks (tasks without parent), and one or more exit tasks (tasks without child). Entry tasks and exit tasks are denoted as \( t_{\text{entry}} \) and \( t_{\text{exit}} \) respectively.

Given a task \( t_i \), its execution time on a resource of instance type \( \text{vm} \text{it}_k \) is denoted by \( ET(i, k) \) and defined as

\[
ET(i, k) = \frac{Z_i}{p_k},
\]

and the data transfer time from \( t_i \) to \( t_j \in \text{succ}(t_i) \) denoted by \( TT(i, j) \) is defined as

\[
TT(i, j) = \begin{cases} 
0 & \text{if } t_i \text{ and } t_j \text{ are mapped of the same VM} \\
\frac{s_{ij}}{\beta} & \text{otherwise}
\end{cases}
\]

The execution cost of task \( t_i \) on a resource of instance type \( \text{vm} \text{it}_k \) is denoted by \( EC(i, k) \) and defined as

\[
EC(i, k) = \left\lfloor \frac{ET(i, k)}{\tau} \right\rfloor \times c_k,
\]

where \( \tau \) is the length of a billing period.

Assuming that a number of tasks \( (t_i, i \in I) \) are mapped onto the same VM instance \( \text{vm}_p \), supposed to be of instance type \( \text{vm} \text{it}_k \), the cumulative execution cost will be evaluated as follow:

\[
EC(I, k) = \left\lfloor \sum_{i \in I} \left\lfloor \frac{ET(i, k)}{\tau} \right\rfloor + \frac{TITS_p}{\tau} \right\rfloor \times c_k,
\]

where \( TITS_p \) (Transfer Idle Time Slots) is the sum of the idle time slots due to data transfer awaited by the VM \( \text{vm}_p \). The example presented in Figure 1 gives an illustration of TITS for the mapping of a DAG of seven tasks onto two VMs. The red rectangles are TITS.

We denote the Earliest Start Time and Earliest Finish Time of task \( t_i \) as \( \text{EST}(t_i) \) and \( \text{EFT}(t_i) \) respectively. They are defined as

\[
\text{EST}(t_i) = \begin{cases} 
0 & \text{if } t_i = t_{\text{entry}}, \\
\max \{ \text{EFT}(t_j) + TT(j, i) \} & \text{otherwise}
\end{cases},
\]

and

\[
\text{EFT}(t_i) = \text{EST}(t_i) + ET(i, k),
\]

where \( ET(i, K) \) is the minimum possible \( ET \) of \( t_i \) over all possible VM instance types.

In like manner, we also consider the Actual Start Time and the Actual Finish Time of a task \( t_i \) mapped onto a VM \( \text{vm}_p \) of instance type \( \text{vm} \text{it}_k \). They are denoted by \( \text{AST}(t_i, \text{vm}_p) \) and \( \text{AFT}(t_i, \text{vm}_p) \) respectively. Their values may be different from those of \( \text{EST}(t_i) \) and \( \text{EFT}(t_i) \), due to the heterogeneity of VMs and the fact that functions \( \text{EST} \) and \( \text{EFT} \) provide the minimum possible value over all possible mapping of tasks onto VMs. The workflow completion time (also called makespan), denoted by \( M_G \), is defined as the Actual Finish Time of the last task in the workflow.

Finally, the total cost of executing a workflow is the sum of the execution cost of all the tasks when effectively mapped onto VMs, and defined as:

\[
Cost_G = \sum_{t_i \in G} EC(i, \text{map}(i)),
\]

where \( \text{map}(i) \) denotes the VM on which task \( t_i \) is mapped, \( 1 \leq p \leq P, 1 \leq k \leq K \).

D. Problem Formulation

The role of a workflow scheduler is to determine an execution order of the workflow tasks, and the VM onto which to assign each task. That mapping of tasks onto VMs have to satisfy some requirements of the user and the cloud provider.

In this paper, the targeted objectives of the workflow scheduler are the minimization of the overall execution cost and execution time, as well as the energy consumption of the system. The constraints are the user-defined deadline (\( \delta \)) and the user-defined budget (\( B \)).

The problem can then be formulated as follow: how to build a workflow scheduling algorithm, able to dynamically provision VMs for tasks execution in order to minimize the overall execution cost and execution time as well as the energy consumption of the system, under of the user-defined budget and deadline?

The problem can be formulated as a mathematical optimization problem:

\[
\begin{align*}
\text{Minimize} \{ & E_{\text{total}} \} \\
\text{Subject to} \ & M_G \leq \delta \land \text{Cost}_G \leq B
\end{align*}
\]

IV. THE PROPOSED SCHEDULING ALGORITHMS

In this section, we present our proposed solutions for the workflow scheduling problem. Here we are presenting two algorithms, Structure-based Multi-objective Workflow Scheduling with an Optimal instance type (SMWSO), and Structure-based Multi-objective Workflow Scheduling with Heterogeneous instance types (SMWSH). Both algorithms are dynamic
and rely on dynamic provisioning. First of all, we present some scheduling techniques used in our proposals, and then their whole description.

A. Determination of the Optimal number of VMs and the Optimal Instance type

Figure 2 shows the structure of a Montage workflow with twenty tasks and their dependencies. In this figure, the left column shows level numbers calculated by equation (13), while the right column is the number of tasks in each level that we call the level width (levelWidth(i)). In this example the largest width is 6 which corresponds to the level 2 (levelWidth(2) = 6).

\[
LN(t_j) = 1 + \max_{t_i \in pred(t_j)}\{LN(t_i)\}, \quad (13)
\]

Obviously, it is unlikely to use more VMs than the largest width of the workflow for its execution. But at the same time how many VMs is suitable for the execution of the workflow? In [17], we have proposed the average width as suitable number of VM to provisioned for the execution of the workflow. In this paper we are using the standard deviation and the maximum width along with the average width (see Eq. (14)).

\[
ONVM(wf) = \begin{cases} 
\frac{AvgW_w}{stdW_w} - \frac{MinW_w}{MaxW_w}, & \text{if } AvgW_w \leq StdW_w \leq MinW_w, \\
\frac{MinW_w}{MaxW_w}, & \text{if } AvgW_w + StdW_w \leq MinW_w, \\
\end{cases} \quad (14)
\]

where \(MaxW_w\) is the maximum, \(AvgW_w\) the average and \(stdW_w\) the standard deviation of the levels’ width of the workflow. For the example of Figure 2, the determination of the optimal number of VMs is presented in Table II.

It is established that instances heterogeneity can easily leads to more energy wastage, due to the workload unbalance of instances. For example, Stavrinides and Karatza [30] studied the impact of the workload and their results reveal that the workload variability has a significant impact on the energy consumption of the system. We also investigated and found that if no careful VM selection is made, using different instances for the execution of a workflow leads to more energy wastage than when one suitable instance is chosen.

Since the optimal number of VMs (\(optNb VMs\)) is determined regardless the type of instance, we can then chose the instance type (\(optInstType\)) which gives better results. The effectiveness of this operation is highly dependent on the estimation of the makespan. Our makespan estimation when using only one instance type \(vmit_k\) (\(estimateM^k_{opt}\)) is made according to equation (15).

\[
estimateM^k_{opt} = \sum_{t_i \in WT} \left\{ET(i, k) + \max_{j \in Succ(t_i)}\{TT(i, j)\}\right\} / optNb VMs \quad (15)
\]

where \(TT(i, j)\) is the transfer time of data from task \(t_i\) to task \(t_j\). An illustration of that estimation is given by Figure 3.

Since their is a parallelism according to the workflow structure, \(optInstType\) is chosen as the fastest instance type \(vm\) which has an estimated makespan that respects the deadline, with an execution cost less than a slice of the budget corresponding to a path \((B/optNb VMs)\). That means, the instance \(vm\) which respects conditions (16) and (17).

\[
estimateM^k_{opt} \leq \delta \quad \text{A} \\leq \text{B} / \text{optNb VMs} \quad (16)
\]

That is the fastest instance type which can respect both the deadline and the budget, according to our makespan estimation and based on the optimal number of VMs (\(optNb VMs\)).

B. Deadline distribution

Since \(minM_G\) is the minimum possible makespan of the workflow \(G\), we can assume the user defined deadline is always greater than \(minM_G\) \(\delta \geq minM_G\). Let be \(EST^{opt}(t_i)\) (respectively \(EFT^{opt}(t_i)\)) the Earliest Start Time (respectively Earliest Finish Time) of task \(t_i\) when executed on \(optInstType\). We define the sub-deadline \(\delta_i\) of each task \(t_i\) as follow:

\[
\delta_i' = \frac{EFT^{opt}(t_i) \times \delta}{\delta_i} = \frac{OPTM_i}{\delta_i + spARE_i}, \quad (18)
\]

where \(spARE_i\) is obtained by distributing the eventual spare time \((\delta - \max_{t_i \in WT}(\delta'_i))\) to all the task proportionally to their length compared to that of the CP.
C. Task priority

The order of execution of workflow tasks is very important in a scheduling strategy. Any ordering strategy used for workflow tasks must take into account the precedence constraints between the tasks. One of the most used ordering strategies is the up-rang of Topcuoglu et al. [22], which has been improved by Wang et al. [31]. In our case, the tasks prioritization strategy is an improved version of [31] and is given by equation (20).

\[
\text{rank}_{u}(t_i) = \sigma_i + \text{outd}(t_i) + \text{OCCW}(t_i) + \max_{t_j \in \text{Succ}(t_i)} \{\text{rank}_{u}(t_j)\}
\]  

(20)

where \(\sigma_i\) is the standard deviation of the computation time of the task \(t_i\) on the available pool of processors. The task with the highest \(\text{rank}_{u}\) is more prioritized.

We are using just the standard deviation instead of multiplying it with the average computation time as it is done in [31]. Furthermore, we are using the average communication cost weight (OCCW) instead of the OCCW, and in addition we are using the out-degree of the task which will grant more priority to tasks having more children.

D. VM Selection and reuse

A task \(t_i\) can be mapped to a VM during the Entry Task Duplication Policy phase (see Section IV-E) or during the Pipeline Merging and Slacking phase (see Section IV-F). Therefore, when a task is selected due to its priority, it is just ignored in this phase, then executed to the already mapped VM at due time.

When a task \(t_i\) is not yet mapped to a VM, the VM selection strategy is a modified version of the one used in HEFT [22]: the VM with the smallest actual finish time determined by finding the first idle time slot capable of holding the task. For SMWSEO, we determine among the already provisioned VMs, the one having the smallest earliest finish time, whereas for SMWSH, it is the VM having the smallest actual finish time under the sub-deadline of the task (\(\delta_i\)). If the corresponding start time is late on the earliest start time of the task, we proceed to the provisioning of a new VM (of type \(\text{optInstType}\)), taking into account the supply time. If the number of already provision VMs is up-to \(\text{optNbVMs}\), we use the VM having the smallest AFT among the available VMs.

if such VM doesn’t exist or the corresponding start time is late on the earliest start time of the task, we proceed to the provisioning of a new VM. The new VM is of type \(\text{optInstType}\) for the case of SMWSEO, and for the case of SMWSH it is the instance that can end faster and under the sub-deadline (\(\delta_i\)). If the number of already provision VMs is up-to \(\text{optNbVMs}\), we use the VM having the smallest AFT among the available VMs. The maximum number of VMs to provisioned is set to \(\text{optNbVMs}\).

E. Entry Task Duplication Policy

The entry task duplication is a technique used to reduce the execution time of the workflow by eliminating transfer time from the entry task [31]. Task duplication can have an impact over the makespan, the cost and the energy consumption. To the best of our knowledge, the entry task duplication selection policies found in the literature does not take into account the case where there are several root tasks in the structure of the workflow. While it help reducing the makespan, it may raise a significant increase of the execution cost and even the energy consumption if the entry task is CPU intensive. It is then necessary to limit the number of duplication and use an accurate duplication policy. In our case, more than one root tasks can be duplicated according to the following policy (see Fig. 4):

1) If totalRepDue = min(\(\text{optNbVMs}, \text{levelWidth}(2)\)) – \(\text{levelWidth}(1)\) > 0, then there may be task duplication;
2) Under the condition (1.), an entry task \(t_i\) can be duplicated if it is the only parent of more than one child (\(\text{nbSingleParentChildren}_i > 1\)). That is, no duplication for children having several parents;
3) Assuming the \(\text{nbSingleParentChildren}_i\) children ordered according to their priority, proceed to a task duplication of the \(\text{nbSingleParentChildren}_i - 1\) first children (\(t_j\)) as long it is possible:
   a) Duplicate \(t_j\) to the VM \(vm_p\) (\(vm_p \in VMS, vm_p <> \text{map}(i)\)) with the lowest execution cost and which fulfills the condition of equation (21)
   \[
   ET(i, vm_p) < ET(i, \text{map}(i)) + TT(i, j)
   \]  

(21)

b) If a such VM \(vm_p\) exists, map \(t_j\) to \(vm_p\) (\(\text{map}(j) = vm_p\))
   c) If not, provision a new VM \(vm_{p'}\) of type \(\text{optInstType}\), map \(t_j\) to \(vm_{p'}\) (\(\text{map}(j) = vm_{p'}\))
4) Assign the first unmapped child (among \(\text{nbSingleParentChildren}_i\) children) to \(\text{map}(i)\);

We will investigate the duplication on behalf of children having several parents in our future work.

F. Pipeline Merging and Slacking

The pipelines Merging and Slacking is a scheduling technique that aim at maximizing resources utilization, reducing energy consumption, and reducing execution cost eventually, through a smart management of sequential and parallel tasks.
A pipeline generally starts from distribution task, ends with an aggregation task, and have a succession of tasks having exactly one parent and one child in the middle. Here, we deal with parallels pipelines, that is a set of pipelines or process tasks coming from the same parent (which is a distribution task) and leading to the same child (which is an aggregation task).

Our Pipeline Merging and Slacking process is in two phases (see Fig. 5). The first phase is to identify parallels pipelines and merge some pipelines in the group, and the second is to apply slack time reclamation to the tasks of some pipelines in each group.

a) Parallel pipelines grouping and merging:: If the current task \( t_i \) is a distribution task (\( \text{outd}(t_i) > 1 \)):
1) Determine whether there are pipelines beginning from one of its children;
2) Construct groups of parallel pipelines;
3) In each group of parallel pipelines:
   a) Determine the longest pipeline (the one having the highest sum of computation length (\( \text{pipeGpL}_{\text{max}} \)));
   b) Constitute sub-groups of pipelines in which the sum of computation length is less or equal to the length of the longest pipeline (\( \text{pipeGpSumL} \leq \text{pipeGpL}_{\text{max}} \));

   The pipelines in the same sub-group could then be mapped to the same VM instance without delaying the execution time, rather, it is possible to have slack times to reclaim.

b) Pipeline Slacking:: The process of the Pipeline Slacking is as follow (see Fig. 6): if the current task \( t_i \) is at the head of a pipeline :
1) Determine the slack time: \( \text{slackTime} = \text{pipeGpL}_{\text{max}} - \text{pipeGpSumL} \);
2) Determine the CPU utilization rate: \( \text{cpuUtilization} = \frac{\text{pipeGpL}_{\text{max}}}{\text{pipeGpL}_{\text{max}} + \text{slackTime}} \);
3) Set the CPU utilization rate of \( t_i \) to \( \text{cpuUtilization} \) using the DVFS technique;
4) For all the other tasks of the current pipeline (subsequent children of \( t_i \)), and all the tasks of the pipelines in the same sub-group:
   a) Map the task to \( \text{map}(i) \);
   b) Using the DVFS technique, set the CPU utilization rate of the task to \( \text{cpuUtilization} \);

The Pipeline Merging and Slacking technique helps in the reduction of the makespan, the energy consumption, and also the execution cost.

G. Description of the SMWSH and SMWSO algorithms

In this section, we present the overall description of the two proposals, named Structure-based Multi-objective Workflow Scheduling with an Optimal instance type (SMWSO), and Structure-based Multi-objective Workflow Scheduling with Heterogeneous instance types (SMWSH). The SMWSO algorithm uses homogeneous instance according to the determination of Optimal Instance type (\( \text{optInstType} \)) described in section \( \text{IV-A} \) and the SMWSH algorithm uses heterogeneous instances. Both algorithms strive to enable the cloud scheduler to spend less money to complete a workflow, while minimizing makespan and energy consumption. While SMWSO consists of five main steps that are:

- The determination of the optimal instance type and the optimal number of VMs as defined in section \( \text{IV-A} \);
- The task prioritization: the workflow tasks are ordered according the their descendant ranku. The ranku if defined in section \( \text{IV-C} \);
- The VM selection and reuse;
- The entry task duplication as defined in section \( \text{IV-E} \);
- The parallels pipelines merging and slacking as defined in section \( \text{IV-F} \);

SMWSH has in addition to those five steps, the deadline distribution (see section \( \text{IV-B} \)). The pseudo-code of SMWSO is depicted in Algorithm 1.

The SMWSH algorithm begins with a VM of instance type \( \text{optInstType} \). But unlike SMWSO, SMWSH handles VM selection, Entry Task Duplication Policy, and Pipeline Merging and Slacking as follow:

1) \text{VM selection}: if the corresponding start time of the VM having the best AFT is late on the earliest start time of the task, a new provisioning is proceeded. It determines the fastest instance type that can execute the task in its sub-deadline;

2) \text{Entry Task Duplication Policy}: in the sub-step \( \text{3c} \) of the task duplication policy, since the VMs are heterogeneous, it determines an instance type that can fulfills the condition of equation (21) and provision a VM of that type.

3) \text{Pipeline Merging and Slacking}: here also because the VMs are heterogeneous, the spare time slacking takes into account the speed of the related VMs;

The pseudo-code of SMWSH is depicted in Algorithm 2.

V. THE TIME COMPLEXITY OF THE STUDIED ALGORITHMS

The REEWS algorithm has a time complexity order of \( O(n^2) \). In fact, as a DAG has in worst case a maximum
Algorithm 1 SMWSO Algorithm

Input: The DAG of tasks
Output: All the tasks are scheduled to their suitable VMs

1: Starting from the \( t_{exit} \), compute \( \text{rank}_u \) for all tasks by using equation (20)
2: Sort the tasks list (\( \text{readyList} \)) in decreasing order of \( \text{rank}_u \)
3: Determine the optimal number of VMs (\( \text{optNbVMs} \)) and the optimal instance type (\( \text{optInstType} \)) as described in Section IV-A

4: for \( t_i \in \text{readyList} \) do
5: Map \( t_i \) to the suitable VM according to the VM selection as described in Section IV-D /*If the number of the already provision VMs is up-to \( \text{optNbVMs} \), we provision no more and we use the VM having the smallest AFT*/
6: Apply entry task duplication over \( t_i \) if needed as described in Section IV-F
7: Apply pipeline merging and slacking over \( t_i \) if needed as described in Section IV-F
8: end for

Algorithm 2 SMWSH Algorithm

Input: The DAG of tasks
Output: All the tasks are scheduled to their suitable VMs

1: Starting from the \( t_{exit} \), compute \( \text{rank}_u \) for all tasks by using equation (20)
2: Sort the tasks list (\( \text{readyList} \)) in decreasing order of \( \text{rank}_u \)
3: Determine the optimal number of VMs (\( \text{optNbVMs} \)) and the optimal instance type (\( \text{optInstType} \)) as described in Section IV-A
4: Provision one VM of type \( \text{optInstType} \)
5: for \( t_i \in \text{readyList} \) do
6: Map \( t_i \) to the suitable VM according to the VM selection policy /*If the number of the already provision VMs is up-to \( \text{optNbVMs} \), we provision no more and we use the VM having the smallest AFT*/
7: Apply entry task duplication over \( t_i \) if needed as described in Section IV-F
8: Apply pipeline merging and slacking over \( t_i \) if needed as described in Section IV-F
9: end for

of \( n(n-1) \) dependencies, and as REEWS uses a clustering technique based on paths determination, we have at most \( O(n^2) \) time complexity.

As for our two algorithms, the phases that must be considered are: task selection and VM selection. For task selection, we need \( O(n^2) \) the Ranku, and \( O(n \log n) \) for tasks sorting. For the mapping, we need \( O(n \times P) \). Since \( P = \text{optNbVMs} < n \), SMWSO and SMWSH algorithms have a complexity of \( O(n^2) \).

Therefore, the three algorithms REEWS, SMWSO and SMWSH have a polynomial time complexity of \( O(n^2) \).

### VI. PERFORMANCE EVALUATION

In this section, we present the experiment’s setup and analyze the simulation results.

We have used the Pegasus workflow generator [32] during experimentation to create the structure of the five real-world scientific workflows (Montage, CyberShake, Epigenomics, SIPHT, and LIGO), in different workload (the number of tasks of the workflow): 50, 100, 200, 500 and 1000 tasks.

To evaluate the performances of our two heuristics, we have implemented them as well as a state-of-the-art heuristic algorithm [10] called Reliability and Energy Efficient Workflow scheduling (REEWS). REEWS aims at minimizing energy consumption and maximizing the reliability of the system in the respect of the user-specified deadline. The choice of REEWS is due to the fact that it uses a (clustering) technique of determination of number of VMs to use, and the DVFS.

Unlike our proposals, the REEWS algorithm relies on static provisioning of VMs. We have not been able to find a single workflow scheduling heuristic, aiming at minimizing energy consumption which uses a dynamic VMs provisioning strategy. Therefore, in order to compare our two algorithms against REEWS, we have designed their static VMs provisioning versions. We have implemented our two heuristic (dynamics and statics versions) as well as REEWS algorithm [10]. The simulations have been done in CloudSim [33]. The performance difference between the static and the dynamic versions of each of our proposal is not significant (1% and 7.48%).

#### A. Experiment Setup

For the simulations we consider the system as a single data center having ten different instance types that are based on the US-east (Ohio) Amazon region [28], collected in July 2019, and which the characteristics are presented in Table III. The last two columns concerning the power were taken from the CloudSim framework [33] modified by Guerout et al. [13].

We have configured the simulation environment as follows. The bandwidth between instances is fixed to 20 MBps, the value of the vCPU of each instance is considered as its processing capacity in Million Instruction Per Second (MIPS) as in [18], and the charging model is hourly based. For the dynamic provisioning of VMs, the provisioning delay of each VM was set to 100 s based on the study by Mao et al. [34].

In the case of experiment with static provisioning, we have
created 10000 VMs such that the number of VMs per instance type is the same. Finally, we suppose that the DVFS is enabled on the different resource.

We have calculated for each the fastest schedule ($FS$) as a baseline schedule and the lowest budget ($LB$) as follow:

$$FS = \sum_{t_i \in CP} ET(i, K), \quad (22)$$

where $ET(i, K)$ is the execution time of task $t_i$ on the fastest instance according to equation (5). $FS$ can be viewed as the sum of the minimum execution times of the tasks belonging to the Critical Path (CP).

$$LB = \sum_{t_i \in G} EC(i, 1), \quad (23)$$

where $EC(i, 1)$ the execution cost of task $t_i$ on the cheapest instance according to equation (7). $LB$ is the lowest possible cost required for executing a workflow, irrespective of the completion time.

Then by using equations (22) and (23), we set variation ranges for user-defined budget and deadline from tight to moderate to relaxed as follow:

$$\begin{align*}
\text{deadline} & = \alpha \ast FS, \alpha \in [4, 8, 12, 16], \\
\text{budget} & = \beta \ast LB, \beta \in [4, 8, 12, 16], \quad (24, 25)
\end{align*}$$

For each of the five workflow and each of the five different sizes (50, 100, 200, 500, and 1000 tasks), we have conducted thirty (30) experiments ($25 \times 30 = 750$). The variation of deadline and budget factors yields 16 different cases. By considering both deadline and budget variations, we have 16 different experiments. The number of experiments is $750 \times 16 = 12000$.

### B. Performance Metrics

We compare the performances of three algorithms REEWS, SMWSO and SMWSH based on the following well-known performance metrics:

- **Cost Ratio (CR):** The CR metric is used to compare the achieved costs of scheduling algorithms. A CR less than 1 means a schedule under the budget (see Eq. 26).
  $$CR = \frac{Cost_G}{B}, \quad (26)$$

- **Time Ratio (TR):** In a similar way, the TR metric is used to compare the achieved times of scheduling algorithms. A TR less than 1 means a schedule under the deadline (see Eq. 27).
  $$TR = \frac{M_G}{\delta}, \quad (27)$$

- **Success Rate (SR):** The SR metric is used to compare the rate of successes of the algorithms (see Eq. 28). There is success when both the CR and the TR are less than 1.
  $$SR = \frac{NB_{success}}{NB_{Exp}}; \quad (28)$$

$NB_{Exp}$ is total number of experiments, and $NB_{success}$ the number of successful schedules.

- **Energy consumption:** The energy in kilowatt-hours (kWh) consumed by the used VMs during the observed time.

### VII. Simulation Results and Analysis

In this section we present and analyze the results of the simulation. We first analyze the results for each of the five scientific workflows used in our experiments. Afterwards, we propose a summarized analysis of the results.

The results are presented via diverse graphs, which show the performance of the different algorithms in terms of CR, TR, SR, and energy consumption. However, in order to do objectives analysis of the results of have conducted statistical tests (ANOVA with Tukey-Kramer post hoc test). Since the energy consumption is highly dependent from the workflow type and from the workflow, the statistical tests have been conducted by workflow and workload. During the simulation, they were a variation of four budget factors (4, 8, 12, 16) and four deadline factors (4, 8, 12, 16). Therefore, for each workload of each workflow, we have 16 different experiments. The summarized statistical tests are given in section VII-F for both SR and energy efficiency.

#### A. Performance for MONTAGE workflow

Figure 7 presents the results obtained for MONTAGE workflow by REEWS, SMWSO and SMWSH. In terms of time efficiency (see Fig. 7b), while our two algorithms, SMWSO and SMWSH always have 100% of schedules in the deadline, REEWS has less than 75% of schedules in the deadline. However, In terms of cost efficiency (see Fig. 7a), SMWSH has about 60% of schedules in the budget while SMWSO and REEWS have 100% of schedules in the budget.

In terms of average success rate, while SMWSO realized 100%, REEWS and SMWSH recorded respectively 80.00% and 62.50% (see Fig. 7c).

We noticed a significant influence of the workload of MONTAGE workflow over REEWS. When the number of tasks increases, the performance of REEWS decreases. That increase in energy consumption observed on REEWS is traceable to the increase of deadline missed due to the workload. In fact, Figure 7c reveals a decrease of the success rate of REEWS due to the workload, and Figures 7a and 7b reveal that REEWS only fails because of deadline violation.

#### B. Performance for CYBERSHAKE workflow

For CYBERSHAKE workflow, SMWSO, SMWSH, and REEWS have a good time efficiency (see Fig. 8b). However, in terms of cost efficiency only REEWS realizes 100% of schedules in the budget, whereas SMWSO and SMWSH have 25% of schedules out of the budget (see Fig. 8b).

In terms of average success rate, REEWS recorded 100% whereas SMWSO and SMWSH realized respectively 78.75% and 85.00%. REEWS is more energy-efficient than SMWSO, and SMWSH for CYBERSHAKE workflow (see Fig. 8d).
C. Performance for EPIGENOMICS workflow

For EPIGENOMICS workflow, SMWSO, SMWSH, and REEWS have 100% of schedules in the budget (see Fig. 9a). However, in terms of cost efficiency only SMWSO and REEWS realise 100% of schedules in the deadline, whereas SMWSH have few schedules out of the deadline (see Fig. 9b).

In terms of average success rate, SMWSO and REEWS recorded 100% whereas SMWSH realized 95.00%.

SMWSO is more energy-efficient than REEWS and SMWSH for EPIGENOMICS workflow (see Fig. 9d). We notice that for the workload of 1000 tasks, SMWSH recorded greater energy consumption compared to SMWSO and REEWS. This was not the case for the smaller workload.

D. Performance for SIPHT workflow

For SIPHT workflow, SMWSO, SMWSH, and REEWS have 100% of schedules in both the budget and the deadline (see Fig. 10a and 10b). Therefore, SMWSO, SMWSH, and REEWS have 100% of average success rate.

REEWS is less energy-efficient than SMWSO and SMWSH.
Fig. 9: Cost efficiency, time efficiency, and success rate (%), Energy consumption of SMWSO and SMWSH vs REEWS for EPIGENOMICS workflow.

Fig. 10: Cost efficiency, time efficiency, and success rate (%), Energy consumption of SMWSO and SMWSH vs REEWS for SIPHT workflow.

for SIPHT workflow (see Fig. 10d). The workload of SIPHT also has significant impact on the energy-efficiency of REEWS.

E. Performance for LIGO workflow

For LIGO workflow, SMWSH has 100% of schedules in both the budget and the deadline (see Fig. 11a and 11b). SMWSO and REEWS have few schedules out of the deadline and 100% of schedules in the budget.

The average of success rate of SMWSH is 100%, whereas SMWSO and REEWS have of respectively 95.00% and 85.00%.

REEWS is less energy-efficient than SMWSO and SMWSH for LIGO workflow (see Fig. 11d). The workload of LIGO also has significant impact on the energy-efficiency of REEWS.

F. Performance summary and discussions

In this subsection, we present a summary of the simulation results and provide some analysis.

1) In terms of success rate: In terms of Success Rate, the three algorithms REEWS, SMWSO, and SMWSH recorded respectively 93.00%, 98.00%, and 88.50% as mean of SR (see Table IVa). SMWSO has higher success rate than the other, with the smallest standard deviation (2.44). However, ANOVA test reveals that REEWS, SMWSO, and SMWSH have comparable performances in terms of success rate (see...
2) In terms of energy efficiency: Since the type and the workload of the workflow highly influence energy consumption, some statistical tests have been conducted by workflow and workload using ANOVA with Tukey-Kramer post hoc tests. The tests results reveal a significant difference between the energy consumption produced by the three algorithms.

Table IV presents the summary of the energy efficiency ranking between the three algorithms REEWS, SMWSO and SMWSH, obtained from statistical tests (you can further explore the determination of the ranking for the case of MONTAGE on Appendix A). It can then be inferred that the REEWS is more energy-efficient or as energy-efficient as our proposals only for CYBERSHAKE (50, 100, 200, 500, and 1000). In all the other cases (80% of cases), our two algorithms SMWSO and SMWSH are significantly more energy-efficient than REEWS.

The results prove the significant improvement of our proposal, the SMWSO algorithm, in terms of energy-saving. We have advocated that:

- Homogeneity can produce better results if good instances are chosen for the execution of the workflow. The out-

| Group      | Count | Sum  | Average | Variance |
|------------|-------|------|---------|----------|
| REEWS      | 25    | 2325 | 93      | 183.33   |
| SMWSO      | 25    | 2450 | 98      | 47.92    |
| SMWSH      | 25    | 2213 | 88.52   | 311.43   |

(b) ANOVA test result

| Source of Variation | SS    | df  | MS    | F-stat. | P-value | F critical |
|---------------------|-------|-----|-------|---------|---------|------------|
| Between Groups      | 1124.51 | 2   | 562.25| 3.11    | 0.05    | 3.12       |
| Within Groups       | 13024.24 | 72  | 180.90|         |         |            |
| Total               | 14148.75 | 74  |       |         |         |            |

performance of SMWSO against SMWSH confirm our statement. In fact, the two algorithms are designed almost in the same manner, apart from the variety of resources used. Both algorithm are sometime more energy-efficient than the other one, almost equitably (see Table IV). However, it is more significant when SMWSO is the best, with a total energy-saving more than 50% better (see Fig. 12).

- If a suitable number of VMs determined, it can help not only to produce better results (in terms of success rate) but also upgrade the VM utilization Maximization and the Energy Consumption Minimization as well as the Workload Maximization. In our two multi-objective algorithms, the optimal number of VMs technique is proposed as an answer to that preoccupation and used to limit the number of VMs to use. The result show that our two algorithms significantly outperform REEWS in terms of energy-saving in most of the types of workflow (apart of Cybershake) and of the workloads.

VIII. Conclusion and Future Work

In this paper, we present the Structure-based Multi-objective Workflow Scheduling with an Optimal instance type (SMWSO) algorithm, aiming at optimizing processing costs, makespan, and energy consumption, under the user-defined budget and deadline in the cloud. SMWSO introduces a new concept, the optimal instance type determination along with the optimal number of VMs, and only uses VMs of optimal instance type. These techniques aim at avoiding resource wastage by determining the optimal type and limiting the number of VMs to provision to an optimal threshold. The employment of the DVFS on non-critical paths have been used to further reduce the energy consumption. Its heterogeneous VMs version denoted as SMWSH has been designed in order to highlight its strength within the heterogeneous environment.
TABLE V: Energy efficiency ranking between the three algorithms REEWS, SMWSO and SMWSH, proceeded from ANOVA with Tukey-Kramer post hoc statistical tests.

| Workflow   | REEWS | SMWSO | SMWSH |
|------------|-------|-------|-------|
| MONTAGE 50 | 3     | 2     | 1     |
| MONTAGE 100| 3     | 2     | 1     |
| MONTAGE 200| 3     | 1     | 1     |
| MONTAGE 500| 3     | 1     | 1     |
| MONTAGE 1000| 3   | 1    | 1     |
| CYBERSHAKE 50| 1   | 3    | 2     |
| CYBERSHAKE 100| 1  | 3    | 1     |
| CYBERSHAKE 200| 1  | 3    | 1     |
| CYBERSHAKE 500| 1  | 3    | 1     |
| CYBERSHAKE 1000| 1 | 3   | 2     |
| EPIGENOMICS 50| 3   | 2    | 1     |
| EPIGENOMICS 100| 3  | 1    | 1     |
| EPIGENOMICS 200| 3  | 1    | 1     |
| EPIGENOMICS 500| 3  | 1    | 1     |
| EPIGENOMICS 1000| 3 | 1   | 2     |
| SIPHT 50  | 3     | 1     | 2     |
| SIPHT 100 | 3     | 1     | 1     |
| SIPHT 200 | 3     | 1     | 1     |
| SIPHT 500 | 3     | 1     | 1     |
| SIPHT 1000| 3     | 1     | 1     |
| LIGO 50  | 3     | 1     | 1     |
| LIGO 100 | 3     | 1     | 1     |
| LIGO 200 | 3     | 1     | 1     |
| LIGO 500 | 3     | 2     | 1     |
| LIGO 1000| 3     | 1     | 2     |

Fig. 12: Total Energy consumption of SMWSO and SMWSH vs REEWS, for all the experiments.

Comparative experimentation have been done through simulations against the state-of-the-art algorithm REEWS. Performance results supported by appropriate statistical tests prove the out-performance of our proposals in terms of energy-saving. SMWSO and SMWSH are more energy-efficient than REEWS in 80% of cases (workflow / workload). Moreover, SMWSO is the more energy-saving, and can save more than 50% total energy compared to SMWSH and REEWS. In terms of user satisfaction, while SMWSO scored at overall the highest success rate, statistical tests proved that their is no significant difference between the three algorithms. This confirms our hypothesis. Firstly, homogeneity can produce better results if a good instance is chosen for the execution of the workflow. Secondly, if a suitable number of VMs is determined, it can help to produce better results.

In our future work, we intend to investigate on the scheduling of multiple concurrent workflows, and also to deal with the uncertainty nature of cloud environments by using machine learning.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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**APPENDIX**

A. Energy efficiency comparison through ANOVA with Tukey-Kramer post hoc tests
### TABLE VI: ANOVA test along with Tukey-Kramer pairwise tests comparing the Energy Consumption of SMWSO and SMWSH vs REEWS for MONTAGE 50, 100, 200, 500 and 10000

| Group   | Count | Sum  | Average | Variance  |
|---------|-------|------|---------|-----------|
| SMWSO   | 16    | 72.16| 4.51    | 8.41E-31  |
| SMWSH   | 16    | 36.16| 2.26    | 8.41E-31  |
| REEWS   | 16    | 131.88| 8.24  | 2.72      |

### ANOVA test result

| Source of Variation | SS  | df | MS  | F stat | P-value | F crit |
|---------------------|-----|----|-----|--------|---------|--------|
| Between Groups      | 292.18| 2  | 146.09| 161.17 | 3.04E-24 | 4.20   |
| Within Groups       | 40.79 | 45 | 0.91  | 2.72   | 5.73    | 0.47   |
| Total               | 332.97| 47 |       |        |         |        |

| Comparison          | Diff | Ab. Diff | Q crit | Is Sig? |
|---------------------|------|----------|--------|---------|
| SMWSO vs SMWSH      | 2.25 | 2.25     | 0.81   | YES     |
| SMWSO vs REEWS      | -3.73| 3.73     | 0.81   | YES     |
| SMWSH vs REEWS      | -5.98| 5.98     | 0.81   | YES     |

#### Algorithm Ranking in terms of Energy saving: SMWSO $\rightarrow$ 2 | SMWSH $\rightarrow$ 1 | REEWS $\rightarrow$ 3

(a) ANOVA test along with Tukey-Kramer pairwise tests comparing the Energy Consumption of SMWSO and SMWSH vs REEWS for MONTAGE 50

### ANOVA test result

| Source of Variation | SS  | df | MS  | F stat | P-value | F crit |
|---------------------|-----|----|-----|--------|---------|--------|
| Between Groups      | 2563.40| 2  | 1281.70| 93.84  | 8.80E-17 | 4.20   |
| Within Groups       | 614.96 | 45 | 13.66 |        |          |        |
| Total               | 3178  | 47 |       |        |         |        |

| Comparison          | Diff | Ab. Diff | Q crit | Is Sig? |
|---------------------|------|----------|--------|---------|
| SMWSO vs SMWSH      | 4.43 | 4.43     | 3.14   | YES     |
| SMWSO vs REEWS      | -12.80| 12.80    | 3.14   | YES     |
| SMWSH vs REEWS      | -17.23| 17.23    | 3.14   | YES     |

#### Algorithm Ranking in terms of Energy saving: SMWSO $\rightarrow$ 2 | SMWSH $\rightarrow$ 1 | REEWS $\rightarrow$ 3

(b) ANOVA test along with Tukey-Kramer pairwise tests comparing the Energy Consumption of SMWSO and SMWSH vs REEWS for MONTAGE 100

### ANOVA test result

| Source of Variation | SS  | df | MS  | F stat | P-value | F crit |
|---------------------|-----|----|-----|--------|---------|--------|
| Between Groups      | 40379.09| 2  | 2019.50| 127.07 | 6.90E-19 | 4.20   |
| Within Groups       | 7457.56 | 45 | 165.72|        |          |        |
| Total               | 47856.65| 47 |       |        |         |        |

| Comparison          | Diff | Ab. Diff | Q crit | Is Sig? |
|---------------------|------|----------|--------|---------|
| SMWSO vs SMWSH      | 8.45 | 8.45     | 10.94  | NO      |
| SMWSO vs REEWS      | -56.86| 56.86    | 10.94  | YES     |
| SMWSH vs REEWS      | -65.31| 65.31    | 10.94  | YES     |

#### Algorithm Ranking in terms of Energy saving: SMWSO $\rightarrow$ 2 | SMWSH $\rightarrow$ 1 | REEWS $\rightarrow$ 3

(c) ANOVA test along with Tukey-Kramer pairwise tests comparing the Energy Consumption of SMWSO and SMWSH vs REEWS for MONTAGE 200

### ANOVA test result

| Source of Variation | SS  | df | MS  | F stat | P-value | F crit |
|---------------------|-----|----|-----|--------|---------|--------|
| Between Groups      | 2649602.10 | 2  | 1324801.05| 81.71  | 1.05E-15 | 4.20   |
| Within Groups       | 7259587.73 | 45 | 16213.30|        |          |        |
| Total               | 13752080.83| 47 |       |        |         |        |

| Comparison          | Diff | Ab. Diff | Q crit | Is Sig? |
|---------------------|------|----------|--------|---------|
| SMWSO vs SMWSH      | 20.64| 20.64    | 108.20 | YES     |
| SMWSO vs REEWS      | -487.75| -487.75 | 108.20 | YES     |
| SMWSH vs REEWS      | -508.40| 508.40 | 108.20 | YES     |

#### Algorithm Ranking in terms of Energy saving: SMWSO $\rightarrow$ 2 | SMWSH $\rightarrow$ 1 | REEWS $\rightarrow$ 3

(d) ANOVA test along with Tukey-Kramer pairwise tests comparing the Energy Consumption of SMWSO and SMWSH vs REEWS for MONTAGE 500

### ANOVA test result

| Source of Variation | SS  | df | MS  | F stat | P-value | F crit |
|---------------------|-----|----|-----|--------|---------|--------|
| Between Groups      | 30446883.33| 2  | 15223441.66| 103.40 | 5.10-17 | 3.20   |
| Within Groups       | 6625787.51 | 45 | 147239.72|        |          |        |
| Total               | 37072670.84| 47 |       |        |         |        |

| Comparison          | Diff | Ab. Diff | Q crit | Is Sig? |
|---------------------|------|----------|--------|---------|
| SMWSO vs SMWSH      | 35.93| 35.93    | 326.06 | NO      |
| SMWSO vs REEWS      | -1671.24| -1671.24 | 326.06 | YES     |
| SMWSH vs REEWS      | -1707.17| 1707.17 | 326.06 | YES     |

#### Algorithm Ranking in terms of Energy saving: SMWSO $\rightarrow$ 2 | SMWSH $\rightarrow$ 1 | REEWS $\rightarrow$ 3

(e) ANOVA test along with Tukey-Kramer pairwise tests comparing the Energy Consumption of SMWSO and SMWSH vs REEWS for MONTAGE 10000

| Source of Variation | SS  | df | MS  | F stat | P-value | F crit |
|---------------------|-----|----|-----|--------|---------|--------|
| Between Groups      | 40890.25| 2  | 102254.12| 64179.03| 5.51E-19 | 4.20   |
| Within Groups       | 13702670.84| 47 |       |        |         |        |
| Total               | 14623061.30| 47 |       |        |         |        |

| Comparison          | Diff | Ab. Diff | Q crit | Is Sig? |
|---------------------|------|----------|--------|---------|
| SMWSO vs SMWSH      | 326.06| 326.06 | 108.20 | YES     |
| SMWSO vs REEWS      | -1671.24| -1671.24 | 326.06 | YES     |
| SMWSH vs REEWS      | -1707.17| 1707.17 | 326.06 | YES     |