Evaluating Distributed Execution of Workloads

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Abstract—Resource selection and task placement for distributed execution poses conceptual and implementation difficulties. Although resource selection and task placement are at the core of many tools and workflow systems, the methods are ad hoc rather than being based on models. Consequently, partial and non-interoperable implementations proliferate. We address both the conceptual and implementation difficulties by experimentally characterizing diverse modalities of resource selection and task placement. We compare the architectures and capabilities of two systems: the AIMES middleware and Swift workflow scripting language and runtime. We integrate these systems to enable the distributed execution of Swift workflows on Pilot-Jobs managed by the AIMES middleware. Our experiments characterize and compare alternative execution strategies by measuring the time to completion of heterogeneous uncoupled workloads executed at diverse scale and on multiple resources. We measure the adverse effects of pilot fragmentation and early binding of tasks to resources and the benefits of backfill scheduling across pilots on multiple resources. We then use this insight to execute a multi-stage workflow across five production-grade resources. We discuss the importance and implications for other tools and workflow systems.

I. INTRODUCTION

The distributed execution of workloads composed of many, possibly dependent tasks poses several challenges. Effective and efficient mechanisms need to be developed to select, acquire, and manage resources along with ways to bind, schedule, and distribute the tasks over those resources. These mechanisms depend on acquiring information about available resource capabilities and workload requirements, and on selecting an appropriate set of resources on which to execute the given workload.

Information acquisition and integration is generally feasible with homogeneous resources and specific types of workloads, but time-dependent availability and heterogeneous resources and workloads add significant complexity. Users and middleware developers resort to use “best practices,” heuristics, or simply trial and error. This leads to suboptimal distributed execution, due to issues such as inefficient resource and task binding, resource under- or over-utilization, lack of data and compute co-location, and minimal data staging preemption.

We address these limitations by devising abstractions and integrating existing middleware. Previously, we used sequences of decisions to model the coupling between workload requirements and resource capabilities [11]. We called these sequences “Execution Strategies”, and used them to abstract resource selection and how the workload’s tasks are distributed on the selected resources.

We implemented execution strategies in AIMES, a pilot-based execution manager which we used to characterize and compare alternative strategies. Differences in the decisions composing a strategy and in the output of each decision correspond to the selection of particular resources with specific capabilities and to a particular binding, scheduling, and distribution of tasks to the resources.

In this paper, we present the integration of AIMES with Swift [2]. While both systems are capable of end-to-end distributed execution of multi-task workloads, AIMES lacks some of the workflow management capabilities offered by Swift, while Swift lacks some of AIMES’s execution coordination capabilities for diverse resources. Among the workflow systems developed to support scientific research [3], we choose Swift because of its modular design, its integration with at least three pilot systems (Coasters [4], Falkon [5], and JETS [6]), and access to its developers. In principle, we could have used any other workflow system or tool implementing distributed execution but we might have incurred in greater engineering effort.

The integrated AIMES and Swift combine their distinctive capabilities enabling the execution of heterogeneous workloads on heterogeneous resources. We describe the integration of the two systems by highlighting architectural and functional difference and similarities. We perform experiments to compare the performance of diverse execution strategies separately with Swift and AIMES, and we profile and emulate the execution of a real-life workflow with the integrated systems.

Analysis of AIMES and Swift, description of their integration, and experimental evaluations contribute towards developing a quantitative model of distributed execution, and offer insight in how to effectively integrate independent middleware components. Many aspects of these advances do not depend on specific workload and resource properties.

II. RELATED WORK

The integration of middleware components to enable large scale, distributed computing is common. Globus [7] and
The TTC of executed workloads approximates their ideal execution strategies against how closely the available resources meet capabilities and their implementations. Quantitatively, we compare execution strategies against metrics that relate to properties of the workload (e.g., duration, size, degree of concurrency), or properties of resources (e.g., hardware type, location), or they might be federation and economic models (e.g., Grid, Clouds, energy consumption, cost of resources, allocation).

For example, for the ‘time-to-completion (TTC) of a workload’ metric, deciding how many and which resources to use relies on models of each resource’s compute performance. Decisions are made by users (e.g., via configuration files), programmers (e.g., via how the application is written), or algorithms (e.g., via runtime decisions).

We compare AIMEs and Swift qualitatively by looking at the decisions of their execution strategies to see differences in capabilities and their implementations. Quantitatively, we compare execution strategies against how closely the TTC of executed workloads approximates their ideal TTC.

III. Architectures

An execution strategy is the sequence of decisions that have to be made to execute a workload on resources. Each decision selects among alternative choices: actions, entities, or attributes, depending on the selection process, workload, and resources. A sequence of choices is a realization of an execution strategy.

Each decision of an execution strategy is based on evaluating how alternative choices satisfy one or more metrics, which in turn are based on models of how choices relate to metrics. These metrics may relate to properties of the workload (e.g., duration, size, degree of concurrency), or properties of resources (e.g., hardware type, location), or they might be federation and economic models (e.g., Grid, Clouds, energy consumption, cost of resources, allocation).

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A. AIMEs

AIMEs enables the execution of distributed applications on HPC and HTC systems. The architecture of AIMEs has three main components: an Execution Manager, a pilot system (‘RADICAL-Pilot’); and a resource information system named ‘Bundle’ (Fig. 1a). The Execution Manager collects information about workload requirements from the application layer (Fig. 1a 1) and both static and dynamic information about resource capabilities from Bundle (Fig. 1a 2).

The Execution Manager integrates information and realizes an execution strategy based on user configuration and dedicated algorithms. Currently, users define the percentage of maximum concurrency with which to execute the workload’s tasks and the percentage of available resources that should be used. Algorithms calculate the amount of resources and the time for which they have to be available, how to partition the resources across pilots, and how to distribute pilots across resources.

This decision process has been empirically tailored to minimize the TTC of bag of tasks (BoT) and multi-stage BoT where subsets of the BoT’s tasks have to be sequentially executed due to data dependences among tasks. The Execution Manager is designed to support the development of alternative decision strategies and optimization metrics. Thanks to a modular design, every decision of an execution strategy can be implemented independently and multiple decisions can be statically (and in the future dynamically) grouped into sequences on the basis of the decisions’ interdependencies and priority.

The Execution Manager enacts execution strategies via RADICAL-Pilot (Fig. 1a 3). A Pilot Manager describes, instantiates, and monitors pilots. Each pilot is submitted to the resource as a job and, once scheduled, executes a Pilot Agent. A Unit Manager translates application tasks into Compute Units, which it then schedules and executes on a Pilot Agent. RADICAL-Pilot uses an interoperability layer called RADICAL-SAGA to access the resources’ batch systems (Fig. 1a 4). RADICAL-SAGA enables pilot submission and data staging over multiple interfaces.

The use of a pilot system enables late binding of workloads to pilots. Late binding is the ability to utilize pilots dynamically, i.e., the workload is distributed onto pilots only when the pilots are effectively available. RADICAL-Pilot is capable of distributing the workload across pilots instantiated on diverse resources. This enables late binding to both pilots and resources: a workload is submitted to a specific resource only when a pilot on that resource is available.

AIMEs is implemented as four Python modules: aims.emgr, the Execution Manager; aims.bundle, the Bundle information system; radical.pilot, the RADICAL-Pilot pilot system; and radical.saga, the RADICAL-SAGA interoperability layer. Each module exposes well-defined or standardized interfaces and can thus be used independently.
For example, both RADICAL-SAGA and RADICAL-Pilot are independently used by diverse scientific communities.

The AIMES components communicate globally via a database service, and locally via distributed messaging. The AIMES Execution Manager and RADICAL-Pilot act in a Master/Worker pattern, as do the RADICAL-Pilot’s managers with regard to the resources’ batch system and the Pilot Agents. This decouples the global and local states of resource selection and execution management. AIMES uses late binding to both pilots and resources to select resources independent of how they will be used for execution.

AIMES maintains a global view of workload execution. The requirements of the workload’s tasks are evaluated before any pilot is described and assigned to a resource. Once evaluated, tasks are scheduled into a global queue controlled by the RADICAL-Pilot Unit Manager. Thus, AIMES can operate on multiple pilots on multiple resources with global scheduling algorithms. These algorithms can, for example, maximize overall resource utilization, prioritize resources, or evaluate resource affinities.

B. Swift

Swift is both a parallel scripting language and a runtime system, used to compose and orchestrate software applications or high-level library functions. There are two implementations of Swift: the original ‘Swift/K’ system [2], primarily intended for local and distributed execution of workflows composed of file-passing applications, and a newer Swift/T system designed to additionally support object-passing functions by running tasks in-memory on large-scale parallel systems. Here we focus on Swift/K and refer to that system as ‘Swift,’ but a similar analysis, integration, and set of experiments could be performed with Swift/T.

The Swift architecture has two main components: an interpreter of the Swift language and a runtime system that executes Swift programs on parallel or distributed resources (Fig. 1b). Swift programs are executed in a two-stage manner. First, a Swift script is parsed and converted into Karajan [20] (Fig. 1b, 1), a declarative-style language with strict evaluation. The Karajan script is then executed by the Karajan workflow engine, which in turn may invoke Swift-specific primitive functions. The Swift runtime system uses a plug-in framework with providers that submit app tasks to diverse computing resources (Fig. 1b 2a and 2b) and that move files to and from those tasks.

The ‘Coaster’ system [4] is a provider that employs the pilot abstraction [15] to allocate computing resources. Pilot are submitted to a computing site’s resource manager (RM) as jobs and, once instantiated, compute node agents (Coaster workers) launch tasks on the nodes and transfer files to and from the node’s local filesystem. In this paper we only consider Swift program execution using the Coaster pilot provider; this is the most common way in which Swift is currently used and is analogous to how AIMES uses RADICAL-Pilots.

Swift schedules app tasks in a multi-stage manner, with responsibility partitioned between the Karajan runtime system and the Coaster pilot execution provider. In terms of execution strategies, this process can be thought of as a sequence of decisions, starting with higher-level scheduling decisions made during language interpretation and ending with lower level decisions made in the pilot scheduler (Fig. 1b).

Swift attempts to schedule tasks to a computing site, controlled by two levels of per-site throttles. At the higher level, each site can, at any given time, accept a certain number of app tasks. At a lower level, Swift also effectively throttles the rate at which tasks can be submitted to the site by limiting the number of concurrently active submission and file management tasks on a per-site basis. Once an app task clears all applicable throttles, the task is queued to the site.

The total number of tasks that can be concurrently queued to a given site can be fixed by the user, or can be dynamically controlled by an automatic site selection algorithm that considers three factors: the number of tasks already queued at the site, the rate at which the site is successfully completing jobs, and the rate (ideally zero) at which jobs may be failing at the site. The dynamic site selection algorithm seeks to simultaneously balance work between sites, assign work based on site productivity, and withhold work to reduce the chances of an app task failing at a site.
Once an app task is assigned to a site, it is enqueued to Swift’s Coaster (pilot) provider and it enters a per-site queue. The pilot scheduler periodically visits each site’s queue to determine the compute node resources needed for that site. The parameters that govern this resource allocation are specified by the user as the maximum number of nodes that can be allocated for the site, and the manner in which that allocation of nodes is grouped into pilot jobs that are enqueued to the site’s resource manager.

Within these constraints, at each scheduling interval the pilot scheduler performs a box-sizing-and-packing algorithm to determine what size pilot jobs need to be submitted (if any) and then what jobs should be packed into each box [4]. Once pilot jobs are started by a RM and compute nodes are provided to the pilot scheduler, the pilot scheduler places app tasks into task slots on the compute nodes through the node worker agents started by the pilot jobs.

IV. Comparison

AIMEs and Swift have overlapping scopes. As end-to-end systems, they both enable users to specify multi-task workloads and execute them on diverse types of resources: Grid, HPC, Cloud. Functionally, users specify and execute applications in different ways on the two systems. These differences are mainly related to workload specification, resource selection, resource partitioning into pilots, pilot and task binding, and task execution. Here we summarize these differences, highlighting those most relevant to the integration of the two systems, which we will describe in the next section.

Workload specification: AIMEs does not offer a native workload description language; users have to use third party languages. These are supported via interface modules that take a workload description as input and return the description of a set of tasks as output. Internally, AIMEs represents tasks as compute units (CU), the same data structure used by RADICAL-Pilot. CUs have a set of predefined properties including, for example, executable, executable’s arguments, number of cores, or message passing interface. Input and output files can be specified for each CU, but limited support is given to the specification of inter-task dependences and to the grouping of tasks in stages or bulks.

Swift is specifically aimed at workflows. The Swift programming language is designed to specify tasks as functions or external executables, alongside their data dependences. The Swift language is implicitly parallel and it includes control structures to describe, for example, the mapping of variables to physical files, the execution of groups of tasks, or the remote execution of specific functions.

Resource selection: AIMEs uses Bundles to obtain static and dynamic information about the capabilities and availability of target resources. This information is polled from the Bundle database via a dedicated API, enabling AIMEs to select resources on the base of both historical and real-time evaluations. For example, a resource may be chosen because its compute and data capabilities satisfy the requirements of the given workload but also because that specific resource has been historically reliable.

Swift enables users to select resources via a configuration file. It can contain an entry for each resource, specifying the parameters required by the execution of their workflow. Users can set the type of Swift provider they want to use with the resource, the address of the resource’s endpoint, the type of resource manager, the data staging modalities, a working directory, and also parameters that determine the parallelism and the concurrency of tasks execution.

Resource partitioning: Both AIMEs and Swift can submit single or multiple pilots with variable cores and walltime to one or more resource. The two systems implement this differently: AIMEs derives the number, binding, size, and duration of the pilots based on the given execution strategy; Swift uses user-provided configuration files or the resource partitioning algorithm described in [III-B].

Resource and task binding: AIMEs enables early binding of pilots to sites and late binding of tasks to pilots. Pilots abstract the capabilities of the resource on which they are instantiated and tasks are bound to a pilot depending on whether the pilot’s capabilities satisfy the tasks’ requirements. For example, a task requiring 128 cores is bound to a pilot with at least that number of free cores, but the same pilot might not be used for tasks requiring large memory.

AIMEs binds tasks only to pilots, not to resources. Tasks are bound to the first available and suitable pilot, independent from the resource on which the pilot has been instantiated. As such, in multi-site executions, not all queued pilots need to be used to execute a workload. Given enough time difference between the first pilot to become active and all the others, all the tasks of a workload could be executed on the first pilot that becomes active.

Late binding to pilots introduces both positive and negative performance trade-offs. For example, distributing multiple pilots across multiple resources reduces the overall time spent in a queue waiting for a pilot to become active [1]. Conversely, late binding to pilots requires more time be spent staging and replicating data across multiple resources.

Swift currently binds some tasks to resources when a site selection algorithm is used, and binds all tasks to resources when the binding is user configured. For multi-site execution, at least a few tasks need to be executed on all the given resources. This behavior could be changed by implementing a different scheduling algorithm for the Pilot Scheduler of the Coaster Provider (Fig. [1]).

Task execution: AIMEs executes workloads by enacting one of the Execution Manager’s execution strategies. The currently available execution strategy requires that all the tasks of the workload are known before starting the workload execution. Consequently, AIMEs cannot execute workloads in which tasks become available after execution has
already started. Currently, AIMES does not support task and data replication, or pilot fault tolerance.

The isolation between the Swift interpreter, workflow engine, and resource providers guarantees the separation of concern between task specification and execution. Swift also enables the separation between the provisioning of tasks and instantiation of pilots. Pilots can be reused when available and scheduled while the the execution is in progress depending, for example, on how a specific site is performing.

V. INTEGRATION

We integrated AIMES and Swift to combine their distinguishing functionalities. This is technically challenging mostly due to the different programming languages used for the two systems. Functionally, the main issues are to account for the differences in how workloads are described and executed, and in the capabilities of the two systems. Specifically, the handling of exceptions and failure, the logging mechanisms, and the state transitions have to be reconciled.

The goal of this integration is to compare the execution strategies implemented by Swift, AIMES, and their combination, not to explore diverse integrative architectures nor to choose the best architecture for a specific metric. For this reason, we developed a prototype of the two-system integration, focusing on those capabilities specifically required by workload execution. Robustness, fault-tolerance, and flexibility are not primary concerns of our prototype.

A main common point of AIMES and Swift is a task-oriented application model [IV]. Both systems assume that a set of tasks is described and then scheduled for execution on suitable resources. The two systems use different task descriptions but both specify the executable to be run on the chosen resource, its arguments, and its inputs and outputs. AIMES also requires specifying the number of cores required by each task and an estimate of the time the task will take to execute. We added this information to the Swift task description.

We developed an interface to enable the two systems to exchange task descriptions (Fig. 2). The interface takes Swift task descriptions as input, translates them to AIMES task descriptions, and outputs them to the AIMES Execution Manager. The interface was implemented via a dedicated provider for Swift (Fig. 2 AIMES provider) and a HTTP-based RESTful API. The use of REST helps encapsulate the resource provisioning logic by implementing it as a persistent service. This approach also helps to bridge differences between Java and Python-based services. The input and output data of the RESTful API are formatted in JSON, describing the application tasks entirely based on their interfaces, which thus eliminates any dependency on the type of language used to develop each system.

AIMES and Swift have different execution models. The Swift provider has no information about the global state of the workflow, with the total number of tasks unknown, as is whether tasks are or will be grouped in stages, with or without current or future data dependences. AIMES requires the whole workload to be known before starting its execution. The RESTful interface enables Swift’s AIMES provider to submit tasks for execution as soon as they are provided by the Karajan Workflow Engine (Fig. 2 1). Meanwhile, AIMES can wait to execute tasks until the task submission rate falls below a certain rate (Fig. 2 2).

This allows AIMES to effectively execute portions of workflows as if they were independent workloads, i.e., a group of independent tasks (Fig. 2 3). For example, given a workflow with two stages, where the input of the second stage tasks are the output of the first stage tasks, Swift submits all the first stage tasks to the RESTful interface and then waits for their output to be available. AIMES does not need information about whether the given group of tasks belongs to a stage, or whether a second stage exists. AIMES monitors the task submission rate to the RESTful interface and, once a configurable amount of time has passed since the last task submission, it executes all the submitted tasks as a self-contained workload.

VI. EXPERIMENTS

We designed two sets of experiments to characterize and compare execution strategies. We executed BoTs and workflows on XSEDE and NCSA resources, studying the effects of strategies’ decisions on TTC. The first set of experiments was executed with Swift and AIMES separately, and the second with Swift and AIMES integrated. All experimental data, code, and analysis are publicly available [21].

Our experiments serve four purposes: (i) to investigate alternative execution strategies to execute workloads of different sizes and types across multiple resources; (ii) to compare the tradeoffs imposed by these execution strategies on TTC; (iii) to outline how design features and configuration parameters enable execution strategies; and (iv) to illustrate how the integration of AIMES and Swift supports profiling and emulation of real-life workflows on distributed and heterogeneous resources.

Each experiment executes an increasingly large BoT or workflow on two to four XSEDE resources and NCSA’s Blue Waters, depending on AIMES, Swift, or their integrated capabilities. We use task and pilot concurrency within and across resources, measuring realistic overheads and tradeoffs.
on production resources. In this way, our experiments are representative of the conditions under which users execute scientific workloads and workflows.

We designed state models for the AIMES, Swift, and integrated middleware, defining the TTC of our experiments as: $TTC = T_x + T_w$. According to these state models, $T_x$ is computed as the sum of the times required by task scheduling, bootstrapping, staging input files (when needed), execution, staging output files (when needed), and shutdown as performed by the pilot on which the task is executed. $T_w$ is computed as the sum of the times required by the AIMES, Swift, or integrated middleware, and queuing pilots on the target resources.

We developed data analysis toolkits to timestamp the start and end of each state of the AIMES, Swift, and integrated middleware [21]. Parsers, filters, and aggregators were used to measure the duration of all the states contributing to $T_x$ and $T_w$ and, therefore, to $TTC$.

We define the performance of an execution strategy as: $P_{ES} = \left( \frac{TTC_i}{TTC} \right) \times 100$. $TTC_i$ is the ideal $TTC$, calculated by assuming maximal task concurrency for the given experimental conditions. Task concurrency depends on the number, size, and duration of the pilots on which the tasks are executed, while task duration is known by design, profiling, or observation. In practice, $TTC_i$ can never be achieved as middleware and resources always impose some overhead, however minimal.

A. Standalone: AIMES and Swift

We performed experiments with Swift and AIMES separately, adopting four execution strategies and executing BoTs of varying size (Table I). The first and second experiment were performed with Swift, the third and fourth with AIMES. Swift’s experiments were performed on Stampede and Gordon, the two XSEDE resources then supported by that system. AIMES’s experiments were performed on Stampede and Gordon, and on Stampede, Gordon, SuperMIC, and Comet.

The execution strategy of Experiment 1 (Table I) maximizes the number of pilots executing the BoT and minimizes the walltime requested for each pilot. Up to 20 pilots (the maximum number of concurrently submitted pilots reliably supported by Swift on Stampede and Gordon), each with 16 cores, were queued on Stampede and on Gordon, enabling a theoretical total of 640 concurrent task executions. Each pilot had enough walltime to execute up to 16 20-minutes long tasks. Each pilot was canceled after being active for 25 minutes, accounting for bootstrap and shutdown overheads.

The effects of this strategy on the $TTC$ of the BoT depends on the availability of resources and the overheads introduced by managing up to 40 concurrent pilots, 20 for each resource. Resource availability is determined by how long the pilots are queued in the site’s RM that, in turn, depends on load and fair share policies. Policies favoring short walltime may result in rapid pilot turnover, near to maximal concurrency, and therefore near to ideal $TTC$. On the contrary, large pilot turnover may also increase management overheads, preventing full use of the available pilots and, as a consequence, increasing the $TTC$ of the workload.

The blue line in Fig. 3 shows $TTC_i$ (ideal $TTC$) for bags of 8, 32, 256, and 2048 tasks. The $TTC_i$ of 8, 32, and 256 tasks is 20 minutes: all the task could be executed concurrently by less than 40 16-cores pilots and the duration of each task is 20 minutes. The $TTC_i$ of 2048 tasks is instead 80 minutes: the given set of pilots can execute 640 tasks every 20 minutes.

The first row of Table I shows the average performance $P_{ES}$ of the execution strategy of Experiment 1. Performance appears to be inversely proportional to the size of the BoT, likely because the execution of smaller BoT requires fewer active pilots on each resource. Fig. 3 confirms this, illustrating how most of $TTC$ is spent in $T_w$. Our analysis of the components of $T_w$ shows that the time spent waiting for the pilots to become active on both Stampede and Gordon queues was the dominant element of $T_w$.

When compared to Experiment 1, the execution strategy in Experiment 2 reduces the number of pilots to between 2 and 32 and increases their walltime to between 75 and 225 minutes (Table I). The smallest BoT increases to 32 as 8 tasks could be executed on a pilot on a single resource while 2048 tasks is kept as the upper boundary. Though the BoT sizes for Experiment 1 and 2 are not the same, they are interleaved, which permits linear extrapolation and thus the claim that the $TTC$ values overlap.

The strategy of Experiment 2 is an attempt to reduce the $T_w$ observed in Experiment 1 by limiting the number of pilots used to execute the BoT. This is done by: (i) reducing the number of concurrent pilots queued on each resource from 20 to 16 for a maximum of 256 concurrent task execution; (ii) Queuing less than 16 pilots for a resource when less than 256 concurrent cores are required to execute the BoT; and (iii) increasing the maximum duration of the pilots so as to allow pilot reuse when supported by the Swift.
The second row of Table I shows that the average $P_{ES}$ of Experiment 2 improves for larger BoTs but worsens for smaller BoTs, relative to Experiment 1. It is difficult to discern this from the $TTC$ averages and the error bars in Fig. 4 and 5 as the two strategies are essentially equivalent. However, with more repetitions, a reduction in errors may indeed indicate that the execution strategy of Experiment 2 performs better.

Analogous to Experiment 1, $T_{w}$ is a significant component of $TTC$ of Experiment 2 (Fig. 4), which is a consequence of both experiments being dependent on the pilot with the longest queue time to become active. Unlike Experiment 1 however, there are relevant systematic errors in $T_{w}$ for Experiment 2.

Configuration parameters used to determine the execution strategies in Swift do not fully control how the tasks are distributed across resources, since the Swift task scheduler.

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Figure 4. Experiment 2. Average $TTC$ and $T_{w}$ for bags of 32, 128, 512, 1,024, 2,048 tasks executed on a total of between 2 and 36 pilots instantiated on both Stampede and Gordon. $TTC_{i}$ of 32, 128, and 512 tasks is 1200 s, of 1,024 is 2400 s, of 2,048 is 4800 s. As in Fig. 3 the error bars of $T_{w}$ (not shown for clarity) are of the same order as those of $TTC$, the large values of which depend upon of fluctuations of the queue time ($T_{w}$) for each pilot on both resources.

**Table I**

EXPERIMENTS PERFORMED WITH SWIFT (1 AND 2) AND AIMES (3 AND 4). T = TASK; R = RESOURCE; P = PILOT.

| Experiment ID | System Name | Workload | #T | T Duration | Execution Strategy | #R | R binding | P binding | P walltime | P cores | #P |
|---------------|-------------|----------|----|------------|--------------------|----|----------|-----------|------------|---------|----|
| 1             | Swift       | 8, 32, 256, 2, 048 | 20  m  | 20  m  | 2 early late 25 m 16 40 |
| 2             | Swift       | 32, 128, 512, 1,024, 2, 048 | 20  m  | 20  m  | 2 early late 75–255 m 16 2–32 |
| 3             | AIMES       | 8, 32, 256, 2, 048 | 20  m  | 20  m  | 2 late late 40 m 4–1024 2 |
| 4             | AIMES       | 8, 32, 256, 2, 048 | 20  m  | 20  m  | 4 late late 80 m 2–512 4 |

**Table II**

AVERAGE PERFORMANCE ($P_{ES}$) OF THE EXECUTION STRATEGIES FOR THE $TTC$ METRIC.

| Experiment ID | $P_{ES}$ per number of Tasks |
|---------------|-------------------------------|
| 8             | 32               | 128               | 256               | 512               | 1024               | 2048               |
| 1             | 22%              | 31%               | 19%               | 7%                |
| 2             | 4%               | 4%                | 3%                | 4%                |
| 3             | 62%              | 77%               | 61%               | 31%               |
| 4             | 46%              | 47%               | 46%               | 33%               |

Figure 5. Experiment 3. Average $TTC$ and $T_{w}$ for bags of 8, 32, 256, 2,048 tasks executed via AIMES middleware on Stampede and Gordon, improved for all the BoTs when compared to those of Experiments 1 and 2. $TTC_{i}$ is 1,200 s for all the BoTs. Note: The Y-axis range is between 0 and 6,000 s in this figure, between 0 and 120,000 s in Fig. 3 and 4.

The execution strategy of Experiment 3 is consistent with the insight gained from Experiment 1 and 2 and with previous experimental results [1]. As each pilot can execute all the tasks to pilots instead of to resources.

Experiment 3 (Table II third row) uses an execution strategy with one pilot for each resource. The size of each pilot is the total number of tasks that need to be executed divided by the total number of pilots that have been scheduled. The duration of a pilot is the time required to execute the complete BoT on the number of cores of that pilot. This strategy minimizes the number of pilots and cores required for each resource, maintaining maximal concurrency only in the best-case scenario in which all the pilots become active at the same time. In the worse-case scenario, the BoT is executed on a single Pilot with as much concurrency as allowed by the number of cores of that pilot.

The execution strategy of Experiment 3 is consistent with the insight gained from Experiment 1 and 2 and with previous experimental results [1]. As each pilot can execute all the tasks of the given BoT, $TTC$ should not depend on the last pilot becoming active, as in Experiments 1 and 2, but on the first one (and on how many pilots become active after the first pilot).

Fig. 5 confirms the reduction of average $TTC$ for Experiment 3 and, as expected, a corresponding reduction in $T_{w}$. The third row of Table II shows an increased efficiency (Fig. 1b) operates this distribution, always binding at least a few tasks to each resource. Experiments 1 and 2 show that this behavior affects $TTC$ on resources with a variable queue time. This behavior could be changed by implementing a different task scheduler, based on matching task requirements to pilot capabilities, as has been implemented in AIMES. We designed Experiment 3 and 4 to characterize and measure execution strategies that use late binding of tasks to pilots instead of to resources.
of the execution strategy used for Experiment 3 when compared to those used for Experiment 1 and 2.

Barring dedicated or largely underutilized queues, queue time of multi-tenant production resources is mostly unpredictable; it depends on per user policies and on the state of the queue at every point in time [22]. Queue waiting time tends to vary over time for each user, and varies differently across resources. The execution strategy of Experiment 3 responds to these fluctuations by submitting pilots to two resources and late binding tasks only to active pilots.

The difference between Experiment 4 and Experiment 3’s execution strategy is that the former uses four XSEDE resources. As the number of resources used increases, the time for the first pilot to become active should decrease. Intuitively, binding tasks only to active pilots should improve with increasing number of resources. However, this improvement must be traded off against the increased overhead of binding tasks to a larger number of resources.

The fourth row of Table I shows an improvement in the average $P_E$ for BoTs with 2048 tasks but a worsening for BoTs with less tasks than 2048. Our analysis shows that this is due to increased overheads of the AIMES middleware in scheduling across four resources, and the very short queuing time of the pilots of both Experiment 3.

Fig. 6 shows average $T_w$, analogous to those in Fig. 5, indicating that the differences in average $TTC$ between Experiments 4 and 3 depend on $T_z$. The communication between pilots and the AIMES Unit Manager via a database service (Fig. 1a) adds overheads to $T_z$: the more resources are used, the higher is the time taken to communicate during the execution of each task [14].

Our experiments were executed in four intervals across three months to sample the behavior of the resources’ queues in different periods. Fig. 5 and 6 show that we experienced very short $T_w$ compared to the historical annual average queue time recorded by XDMoD [23]. In presence of longer $T_w$, Experiment 3’s execution strategy could perform worse than Experiment 4’s due to the reduced interplay between the queue times of just 2 resources, which would be consistent with previous data [1].

B. Integrated: AIMES and Swift

We used the insight gained from the comparison of alternative execution strategies to perform experiments with the integrated Swift and AIMES middleware.

Fig. 7 shows a workflow developed within the ExTASY [25] project and used to execute a Simulation Analysis Loop pattern. The workflow is used to model a solvated alanine dipeptide molecule containing 2,881 atoms. Each simulation executes the Amber MD Engine for 0.6 ps followed by analysis of all simulations [24]. The workflow comprises four stages, two for the simulations and two for the analyses. Stage 1 has $N$ 1-core simulation tasks, each taking the three input files of the workflow and returning one output file. Stage 2 is comprised of $N$ 1-core simulation tasks, each taking one output files of Stage 1 and two input files of the workflow, and returning one output file. Stage 3 consists of one MPI analysis task with $N$ cores, taking all Stage 2 output files and one input file of the workflow, and returns $N$ output files. Stage 4 executes one analysis task with one core, taking all output files of Stage 3 and one input file of the workflow, and returns a single output file.

We used Synapse [26] to generate emulated tasks that have the performance of ExTASY tasks. We then executed the ExTASY workflow with 256 to 2,048 simulations, using Experiment 4’s execution strategy. We used up to five resources: four from XSEDE and Blue Waters. We measured average $TTC$ at each scale and utilized the analytical tools we developed for both AIMES and Swift to measure the $TTC$ time components.

Fig. 8 shows a progressive increase of both $TTC$ and $T_w$ averages. Our analysis shows that $TTC$ increases mainly due to the time taken to stage input and output files between the user’s workstation and the resource of the pilot on which each task is executed. While input and output files are on average few hundred KB, their number increases with the scale of the workflow. The progressive increase of $T_w$ is due to a corresponding increase in the pilots’ average queue time. This likely depends on the size of the requested pilots: the larger the number of tasks of the workflow, the larger
time low. Similar to Experiment 3 and 4, this is obtained by binding to active pilots and a reduction in the typical time for the activation of the first pilot.

Rows 4 and 5 of Table II show that the same execution strategy can perform differently depending on the type of workload executed. The same strategy performs well with the BoT used for Experiment 4 but poorly with the workflow used for the integrated experiments. This depends on file staging, required by the integrated experiments but not by Experiment 4; data are staged in and out of remote resources for each task during execution. This adds overhead to $TTC$ but it is necessary as, currently, the AIMEs task scheduler does not schedule tasks to a pilot based on whether their input data are already available to that pilot.

The explicit definition of the execution strategy allows us to isolate the decisions that affect the performance of the execution for the $TTC$ metric. For example, an execution strategy with a single resource and an early binding of tasks to that resource could be used for the integrated experiments. This would avoid intermediate data staging between the user’s workstation and the resource, and enable a comparison between the two alternative strategies.

VII. Conclusions

Distributed execution of heterogeneous workloads on heterogeneous resources opens a large problem space with both conceptual and implementation challenges. We focused on the issues of deciding among alternative ways to distribute executions and on comparing their performance using the notion of an execution strategy. We described, compared, and integrated AIMEs and Swift; then we used these systems to analyze the performance of four execution strategies with two types of workloads, at different scales, and on multiple and diverse resources.

Our comparison of AIMEs and Swift uncovered their architectural and functional analogies and differences (§IV and §V). The same core features enable the two systems to perform distributed executions but because of their diverse capabilities, they enact these executions differently. Task-based workload description and pilot-based abstraction of resource capabilities enable distributed execution, but different ways to bind tasks to resources or schedule tasks to pilots leads to different realizations of the execution. In this way, we reiterate that the challenge is not engineering distributed execution but characterizing and measuring alternative ways to distribute those executions.

Our contribution is to advance and extend the concept of execution strategy [1]. We integrated Swift and AIMEs into a system specifically designed to execute, characterize, and measure alternative execution strategies (§V). From an implementation perspective, our integrated prototype confirmed the benefits of a RESTful API but, more importantly, it showed how to reconcile diverse approaches to workload management and disjoint state models, without re-engineering AIMEs or Swift.

Our experiments compared and measured the performance of four alternative execution strategies (Table I). We contributed a definition of the performance of execution strategies ($P_{ES}$) based on observed and ideal $TTC$. The performance differences between Experiments 1–2 and 3–4 show the relevance of resource availability on distributed executions (Table II). We explained this by showing the dominance of $T_w$ and importance of responding to different queue time across multiple resources (§VI–A).

The performance differences between Experiment 4 and the experiments using the integrated AIMEs and Swift system showed how the performance of execution strategies also depends on the characteristics of the executed workload (§VI–B). By introducing data staging, the execution strategy of Experiment 4 performed more poorly that the integrated experiments. We clarified that this was not due to the size of the file transferred, but a byproduct of how late binding to pilots is implemented. This was reflected in the values of $P_{ES}$ for the integrated experiments (Table II).

This work indicates several directions for future research. Conceptually, the notion of execution strategy needs to be generalized to provide greater quantitative insight, and its use extended to more systems and more use cases. To test the validity of the execution strategy abstraction and to stress its generality, we plan to explore its integration with PANDA-WMS, the primary workload management system for the ATLAS project. Investigating these and other trade-offs will be the subject of future research.

The AIMEs and Swift integration will be further developed. Currently, the integrated prototype enables execution but offers limited introspective capabilities. Swift’s and
AIMEs’ state models cannot be fully coordinated due to the limitations in how information is shared between the two systems. Thus, no error management, fault-tolerance, or shared logging is available during execution. Extending the RESTful API to exchange information while maintaining the separation of concerns between the two systems will be a core requirement for developing a production-grade integration between AIMEs and Swift.

The integration of Swift and AIMEs provides a preliminary case study of effective integration between independent tools that enable distributed computing. We believe more case studies are needed to understand how to reduce the number of redundant and competing tools and thus create a sustainable software ecosystem.

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