A Model for Simulation of Application and Resource Behavior in Heterogeneous Distributed Computing Environments

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Abstract: Accurate modeling of the behavior of resources and scientific applications in distributed computing environments is complicated by factors such as resource heterogeneity, variability, and volatility. In this work we present a simulation model for fine-grained simulation and analysis of resource environments composed by multiple types of distributed computing resources. The simulation model is based on simulation of individual computational resources and emulation of virtual infrastructures and resource environments. Application and resource behavior are modeled in behavior profiles that capture the wide variability of distributed computing applications and resources, and allow modeling of non-standard metrics such as heterogeneity, variability, and volatility of resources and resource environments. Around the behavior profiles, virtual infrastructures are emulated using discrete-event simulations where infrastructure components are independently modeled. The design of the framework is aimed to facilitate both verification of middleware and application software as well as experimentation with prototype infrastructure components.

1 INTRODUCTION

Distributed computing environments are becoming increasingly heterogeneous and complex, and application and resource behavior are becoming harder to model and predict. A number of concurrent developments contribute to this phenomenon, for example:

- integration of multiple resource types, e.g., shared and dedicated resources, in resource pools
- emergence of heterogeneous hardware platforms that combine different types of computational resources, e.g., on-chip CPU and GPU resources
- development of energy efficiency techniques that allow CPUs to disable or vary the speed of cores
- provisioning of computational power as services running virtual resources in compute clouds

Precise prediction and modeling of application and resource behavior is of great interest in design and construction of virtual infrastructure components and tools for distributed computing. However, there is currently a lack of simulation toolkits that are capable of encompassing the heterogeneity and volatility of resource (and application) behavior in heterogeneous distributed computing environments.

In this work we propose an approach to discrete-event simulation of heterogeneous distributed computing environments based on profiling of computational applications and resources combined with emulation of resource environments. In addition, we also present preliminary findings from a prototype implementation of a simulation framework based on the model, and demonstrate the feasibility of the approach in a brief performance evaluation. The simulation model is designed to be simple and computationally efficient, yet flexible enough to accurately model resource and application behavior (including failures and varied availability) realistically.

The intended use case of the model is to create a simulation framework that allows modeling of application and resource behavior in mixed resource type environments. As mixed resource environments have unique compositions that may vary over time, the framework emphasizes a simple and robust behavior model coupled with an environment emulation toolkit over generic resource environment models.

The proposed simulation model is intended to model application and resource behavior at a very fine level, while providing a generic interface to an emulated distributed computing environment. The goal of this approach is to provide a tool that allows existing mechanisms to be integrated in an emulated environment and evaluated without modification.

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A number of distributed computing simulation toolkits exist, e.g., SimGrid (Casanova, 2001), GridSim (Buyya and Murshed, 2002), and MICROGRID (Song et al., 2000) for grid computing. For cloud computing there exists a set of resource environment simulation tools including CloudSim (Calheiros et al., 2009), iCanCloud (Nuñez et al., 2011), GreenCloud (Kliazovich et al., 2010), and CloudStone (Sobel et al., 2008). For evaluation of production tools some systems, e.g., OpenNebula (Milojičić et al., 2011), support execution in simulation mode, which allows experimentation for integration and prototype evaluation. However, as these systems are oriented around specific infrastructure types, they make strong assumptions about the behavior and construction (homogeneity, capacity consistency, etc.) of resources and resource environments.

While the more generic models exposed by these tools are sufficient for modeling of infrastructures built on a single resource type, the assumptions they are based on make it hard to capture fine-grained analysis of resource behavior in multiple resource type environments. On the network side, tools such as Superna (Superna Network Planning Engine, 2012) and OPNet (Chang, 1999), allow modeling of throughput and capacity of networks. Integration of these in modeling of resource behavior is however difficult as these tools generally only consider network as a resource.

A large amount of general simulation and modeling toolkits, ranging from service-oriented modeling frameworks (Tsai et al., 2006) to tools such as LoadRunner (Booth et al., 2007) also exist. These tools are very efficient for construction of simulation models and modeling of specific phenomena such as resource load, but again these are hard to use in integration of multiple models for evaluation of infrastructures. The model proposed in this work is focused on a specific use case, modeling and analysis of resource behavior in distributed computing environments. As such, it aims to facilitate development of computational tools and components for virtual infrastructures for distributed computing.

The rest of this paper is structured as follows. Section 2 introduces the simulation model of the framework, and details the modeling of individual applications and resources as well as the computational model used in resource simulations. Section 3 presents a brief performance evaluation to demonstrate the feasibility of the approach and illustrate the computational performance of the model. Finally, Section 4 discusses the contributions and the results, and Section 5 concludes the paper.

2 SIMULATION MODEL

Traditional application performance metrics are primarily concerned with the characteristics of computational resources and how well applications make use of available resource capacity. However, when viewing application performance from a virtual infrastructure perspective (and considering metrics such as application computational throughput), factors such as resource availability, resource predictability, and application fault tolerance become more important. Factors such as these are not easily captured by performance-oriented metrics, but require a model that allows heterogeneity and volatility in resources and variation of resource behavior over time.

The model of this simulation framework is concerned with capturing the *behavior* (as seen from the virtual infrastructure perspective) of computational applications and resources, rather than the performance and characteristics of the applications and resources themselves. Hence, the primary focus of modeling lies on the computational throughput, here defined in terms of provided and utilized resource capacity over time. The model presented here is based on definition of capacity profiles for individual dimensions of resource capacity (e.g., computational or network transfer capacity) and combination of application and resource profiles to compute the throughput of applications on resources.

The computational model of the simulation framework proposed here is for reasons of computational efficiency simple. The expressive power of modeling resource and application behavior in profiles, and use of these to simulate computational throughput, is however strong enough to encapsulate the wide and varied behavior of computational resources in distributed computing environments.

2.1 Application Behavior Profiles

To model application behavior over time in a fine-grained yet computationally efficient way, we define a model of application behavior that characterizes required task processing capacity in quantifiable dimensions, e.g., network, computational (CPU), or storage capacity. The capacity usage is measured at finite periodical time steps and quantified relatively against maximal capacity. As illustrated in the left part of Figure 1, which details an example one-dimensional application profile, the value space of capacity profiles is $[0, 1]$. For scaling and comparison between profiles, profiles are assigned a weight to scale the profile to comparable resource capacities.

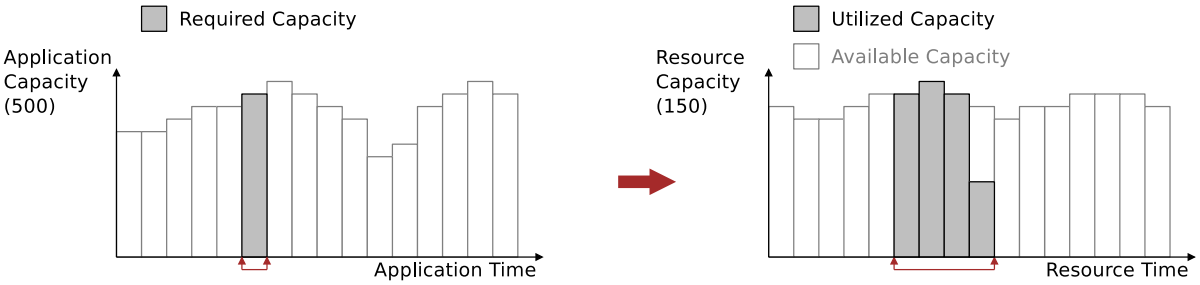


Figure 1: Capacity integration.

2.2 Resource Behavior Profiles

To predict and simulate infrastructure behavior, a simulation model requires not only a model of application behavior, but also one of resource behavior. Like their application counterparts, resource behavior profiles can be formulated by characterizing the amount of resource capacity provided (in individual dimensions) over time. While the behavior of individual computational resources may be stable and conform to predictable patterns, the behavior variations between different types of resources will vary greatly in distributed computing environments, implying that different resource types should modeled independently.

For interpretation, application profiles can be seen to express minimum requirements for capacity, while resource profiles express upper bounds (maximums) for provisioned capacity. Interpretation of resource profiles requires a semantic for modeling failures.

2.3 Resource Behavior Simulation

The majority of the distributed computing applications in use today perform computations in the form of batch jobs, i.e. batch executions of programs. From a simulation point of view, this is attractive as batch jobs imply distinct phases and lifetimes for computations. The model for batch computation used here defines four (resource-oriented) phases for a job:

- stage in (transfer of data to resources),
- queue wait time,
- execution,
- stage out (transfer of data from resources).

In addition to these, jobs will naturally go through other phases in, e.g., batch queue wait and scheduling cycles. As these are not part of the local resource queue processing phases, they are not considered in the core resource simulation.

For calculation of the computational throughput of an application on a resource, the proposed simulation framework matches the capacity required by applications with the capacity provided by resources to estimate the processing time of a job task. The total capacity required by an application is divided into discretely sampled timesteps, and the capacity of each time step is matched against the discretely sampled capacity provided by a resource, as illustrated in Figure 1. A configurable constant is applied to scale the required resource capacity to the metrics used in the simulation, e.g., CPU seconds. As application profiles and resource profiles are scaled independently, a single application profile time step may result in utilization of multiple resource time steps.

In simulation of the resource processing of tasks, the resource capacity profile is sampled at finite timesteps and summed until the (by the application) required resource capacity is met in each dimension. In the discrete case, this means that a formulation like Algorithm 1 is used in implementation.

Algorithm 1: Capacity integration.

```
Input: Application profile appProfile
Input: Resource profile resProfile
Output: Estimated application run-length

timesteps = 0;
foreach time step t in appProfile do
    foreach dimension d in appProfile do
        capacity_a = appProfile(t,d);
        capacity_r = 0;
        nrT(d) = 0;
        while capacity_r < capacity_a do
            capacity_r += resProfile(nrT(d),d);
            nrT(d) += 1;
        end
    end
    timesteps += max(nrT);
end
return timesteps * sizeof(time step);
```

As modern computers contain hardware constructs that allow overlapping of network transfers and computations with little performance degrada-

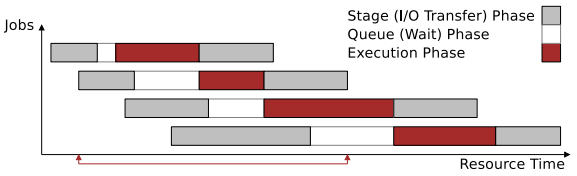


Figure 2: Execution pipeline of a local resource queue.

tion, the simulation framework employs a model where jobs can perform staging of data in parallel with execution of other tasks in the local resource queue. For the simulation, this means that resource capacity is integrated in at least two dimensions (network transfer and computational capacity) for the four distinct task processing phases, and that the total job completion time will be made up by four components as illustrated in Figure 2. Note that while the integration of application and resource capacity is performed as a discrete-time simulation, the computational results from this process is fed to a discrete-event simulation of the resource queue processing pipeline. Using this simple computational model, an estimation of the processing time for each task execution phase is established. The estimated processing times for jobs are then used to offset time steps in discrete-event simulations of virtual infrastructures.

As the simulation of individual resources is independent of the simulation of other resources, simulation is embarrassingly parallel and can be performed concurrently. Resource simulations are grouped and queued in computational task bins, which are orchestrated by a coordinator in the simulation engine. Note that construction (and evaluation) of application and resource profiles are independent of resource simulation, and can be performed in advance or on-demand by the simulation process. The entire simulation process is highly parallel, and consists of multiple computationally cheap and independent tasks that can be efficiently implemented using concurrent programming constructs such as multi-threading on multi-core machines, or (with modification of the simulation coordinator) be distributed over multiple machines.

2.4 Modeling of Resource Types

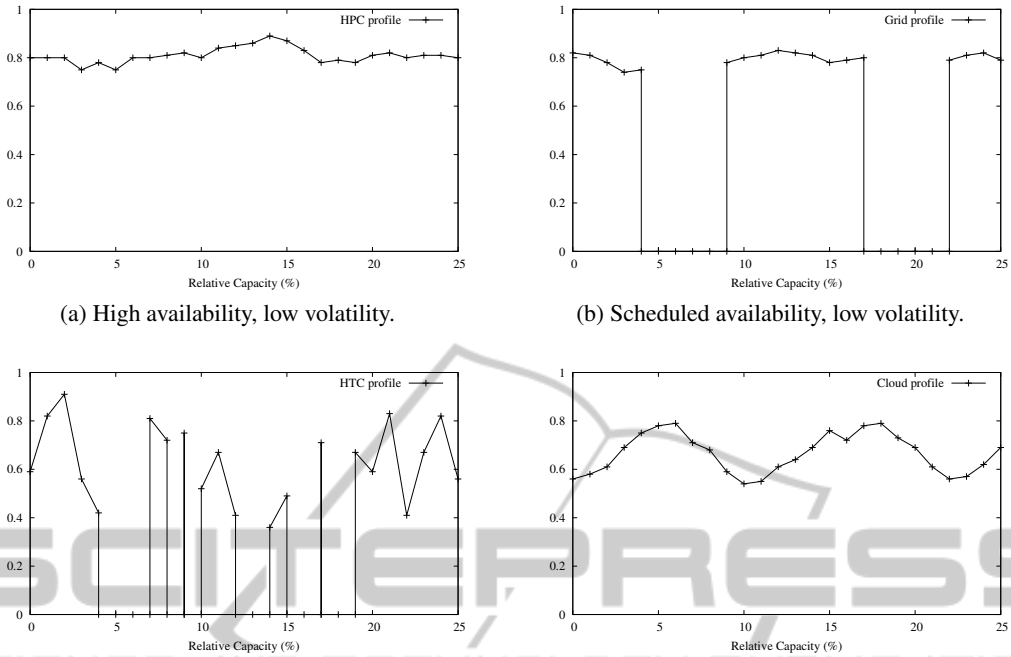
While the model described in Section 2.3 is computationally very simple, the expressive power of modeling resource behavior using capacity profiles is great. Variability in behavior profiles describes not only fluctuations in resource capacity, but also indirectly discontinuities such as variations in availability and volatilities due to errors.

Using this model, the behavior of distributed computing resources can be classified by, e.g., resource type, availability schedule, and volatility. One of the primary indicators of overall resource behavior is resource type. For example, well maintained dedicated computational resources such as High-Performance Computing (HPC) servers typically exhibit fairly constant performance and high availability under stable load. Resource Grid (Foster and Kesselman, 2004) machine pools (typically constructed through collaborative interconnection of dedicated HPC resources) will exhibit similar behavior, while being subject to more restrictive availability schedules.

Shared computational resources such as volunteer computing (Sarmenta and Hirano, 1999) or desktop grid (Chien et al., 2003) resources are however harder to model, as they exhibit high seasonality in availability (e.g., with increased availability during nights and weekends) and higher volatility in both load and performance. Shared resources are subject to different types of resource contention than dedicated resources, which can lead to unpredictable behavior and volatility. Modeling of virtualization-based resources such as cloud computing (Armbrust et al., 2010) resources is easier from an availability perspective as virtualized cloud resources are instantiated on demand, but can (due to resource contention on the underlying hardware level) instead exhibit higher variations in resource performance (Ostermann et al., 2010).

In addition to resource type and availability, resource volatility is also a factor with substantial impact on overall resource performance. In this concept we here include factors such as natural variations in resource capacity (e.g., network bandwidth variations due to medium contention), unscheduled variations in resource availability (e.g., job preemption forcing check-pointing in volunteer computing environments), and hardware and software errors. In general, shared computational resources exhibit higher volatility than dedicated resources as they present more heterogeneous environments with greater variability in (and less predictable) performance. Shared computational resource pools are also more likely to be constructed using commodity computer components running greatly varied software stacks, and are as such more prone to hardware and software errors.

Figure 3 presents four resource behavior profiles that are here used to illustrate differences in resource behavior between resource types. Figure 3a illustrates the behavior of a dedicated, well-maintained high-end computational resource with stable load. This type of behavior profile well encapsulates the behavior of dedicated HPC resources with high uptime and infrequent hardware errors. Similarly, Figure 3b illustrates the behavior of a dedicated resource with scheduled availability, e.g., a resource grid machine. In contrast



(a) High availability, low volatility.

(b) Scheduled availability, low volatility.

(c) Varied and seasonal availability, high volatility.

(d) High availability, low volatility.

Figure 3: Variations in resource behavior profiles.

to these, Figure 3c instead illustrates the behavior of a shared computational resource with high seasonality in availability, and high volatility in capacity during the shared time periods. Finally, Figure 3d illustrates the behavior of a virtualization-based resource that exhibits high availability, but with more or less periodically varied capacity.

The differences between these types of resource behavior well describes the challenges of construction of virtual infrastructure components, such as meta-scheduling and brokering systems, in mixed resource type environments. To enable efficient modeling of resource behavior in such heterogeneous environments simulation tools need to capture variations in resource behavior, including multi-dimensional heterogeneity, not just performance.

To fully model resource behavior, simulation frameworks also needs to apply some level of interpretation to behavior profiles in resource simulation. For example, simulation of a resource with high volatility of a nature that can cause job preemption should incorporate information of whether the application supports (and induces overhead from) checkpointing in resource simulations. To encompass such differences, we propose that simulation frameworks expose resource simulation algorithms as customization points, so that resource simulation implementations can be replaced using third party plug-ins.

3 EVALUATION

For the purpose of this evaluation, to demonstrate use and characterize the computational performance of the simulation model, we consider a two-dimensional performance metric that contains application and resource profiles for computational and network transfer capacity. To illustrate the computational performance of the framework, we construct four sets of tests that combined demonstrate the scalability of the simulation model and the computational efficiency of the framework. To demonstrate the scalability of the model we simulate a simple HPC-based virtual infrastructure and vary the amount of jobs, the amount of resources, and the time step in simulations. To demonstrate parallelization of the model, we then run a set of tests where we vary the amount of threads used to simulate the resources in the simulation.

3.1 Test Environment

For ease of analysis, all evaluation tests are performed on the same machine where the simulation engine is the only load process in tests. The testbed consists of a quad Intel Xeon X3330 2.66GHz with 7GB RAM running 64 bit Ubuntu v11.04 interconnected with a 1 Gbps Ethernet network. The Java version used in tests is Sun Java 1.6, and Java memory allocation pools

range from 512 MB to 1 GB in size.

3.2 Evaluation Tests

To demonstrate the resource simulation mechanics, we define a simple environment model of an HPC cluster consisting of a job queue (that in tests is fully saturated at all times), a scheduler (that performs a simple round robin scheduling algorithm), and a set of computational resources with fully saturated resource queues. In experiments we run a set of jobs with a predefined simulation time step and a fixed set of resources to simulate. We then vary the different parameters (simulation time step, number of resources, number of jobs) to investigate how the simulation framework scales versus the simulation parameters. To compensate for natural variations in simulation accuracy due to machine load and performance variations, all experiments are repeated at least ten times and data presented is based on average experiment values.

3.2.1 Varied Time Step

In the first experiment we vary the time step used in simulation. Use of a smaller time step in application and resource behavior profiles allows for more fine-grained simulation of behavior, but increases the computational load of the simulation. As can be seen in the graph of Figure 4a, decreasing the application time step (increasing the amount of time steps per job) increases the amount of computations linearly in the experiment.

3.2.2 Varied Amount of Jobs

In the second experiment we vary the amount of jobs used in simulation. As in the case of increasing the time step resolution, increasing the amount of jobs will also increase the computational burden of simulations. In essence variation of these two parameters yield the same result, more application timesteps to translate to resource timesteps. As illustrated by the first (single-thread) graph of Figure 4b, increasing the amount of jobs to run linearly increases the amount of timesteps to run, and also the computational cost of the simulation.

3.2.3 Varied Amount of Resources

In the third experiment we vary the amount of resources used to simulate a fixed set of jobs. In this experiment we do not observe any major fluctuations in the computational cost of simulations (compared to the experiment illustrated in Figure 4a). This stems from the computational burden of a simulation depending on the number of application timesteps. As resources are simulated independent of each other, variation of the number of resources will not majorly affect the computational burden of the simulation of resources. Inclusion of higher level components of virtual infrastructures such as schedulers will naturally be affected by the inclusion of more resources.

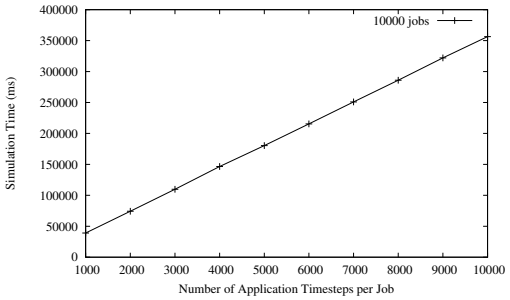
3.2.4 Parallelization

As a final experiment in the analysis of the behavior of the model, we repeat the previous experiment but now bundle the resources in spatially segmented groups of resources that are each simulated in separate threads. As illustrated in Figure 4b, resources that are simulated independently of each other are parallelizable and the total simulation time can therefor be reduced through parallelization. As illustrated in the figure, the system suffers some overhead from management of thread pools that limit the scalability of the model. Further analysis of ways to improve the scalability of this model, including distribution of the simulation communication to allow processing of the resource simulation on multiple computational resources is subject for future work.

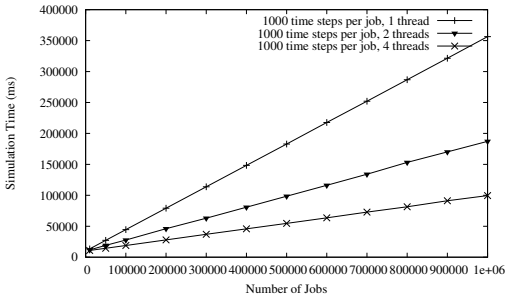
3.3 Results

As demonstrated in tests, the computational cost of the model scales with the amount of timesteps performed in resource simulation. Reducing the time step size in resource simulation increases simulation resolution, but also the amount of computations required for simulations. Increasing the amount of jobs simulated also increases the required amount of computations, while increasing the amount of resources (without increasing the amount of jobs) does not impact the amount of computations much. As resources are simulated independent of each other (and grouped to match the amount of hardware threads available), increasing the amount of threads used allows for near linear scaling of the performance of the model.

Quality-oriented tests, that more extensively measure simulation model ability to capture the behavior of real applications and real resources are planned and subject for future work. For this contribution however, extensive studies of construction of application and resource profiles are deemed out of scope. In the evaluation, we perform only simulations of artificial resources and models, i.e. with synthetic profiles for applications and resources. In tests we use simulated profiles composed of the application and resource model base functions described in Figure 3.



(a) Simulation time (ms) as a function of time step size.



(b) Simulation time (ms) as a function of number of jobs.

Figure 4: The scalability of the computational model.

4 DISCUSSION

With the application behavior profile formulation of Section 2.1, example profiles that model basic (e.g., cyclic or bursty) application behavior are easily constructed for resource simulation purposes. For simulation of application behavior, sophisticated application behavior profiles can be developed through methods such as application profiling (Feng et al., 2005), analysis of workload traces from archives such as the parallel workloads archive (Feitelson, 2007) and the grid workload archive (Iosup et al., 2008), or by use of external monitor tools that measure application behavior through operating system constructs (Morshed and Meagher, 2004). Naturally, measurements of application behavior should be performed on stable, high-performance resources to minimize the influence of variations in resource behavior. While development of accurate models for application behavior is of great interest for the purposes of this work, it is deemed out of scope for this contribution as the focus here is the simulation model.

It should be noted that not all applications behave as described in Section 2.3. With the increased popularity of cloud computing, where virtual machines are enacted as services (instead of programs executed as batch jobs), the balance of application-resource behavior changes substantially. Modeling of the behavior of computational applications and resources in virtualization-based environments is subject for future work, but considered out of scope for the current contribution as these phenomena are not captured by the current environment and process model.

For development of descriptive resource profiles, which is an area of great interest to, e.g., meta-scheduling and distributed computing broker frameworks, a number of tools can be used to quantify resource behavior. Common approaches here include, e.g., running pilot jobs that benchmark resources, or performing analysis of run-time logs for applications. While the peak computational capacities of resources can be measured with great accuracy, actual provided capacity will vary with a number of factors such as load, availability schedules, and (hardware and software) failures.

The network capacity of resources will like computational capacity have a quantifiable peak, but will likely exhibit higher variability as it is subject to not only local resource contention but also to contention of shared (bandwidth) capacity with other resources. To reduce complexity in modeling, we here model network capacity for each resource independently. For construction of accurate models of network behavior, a number of approaches ranging from measurements using tools such as iPerf (Tirumala et al., 2005) to historical analysis of logs exist.

Development of sophisticated models for application and resource behavior is of interest and subject for future work. For example, to model application behavior in cloud environments, it is expected to be of interest to be able to assign cost functions for transferring data in and out of (commercial) clouds.

As the simulation framework exposes customization points for all modeled infrastructure components and simulation algorithms, more advanced (multi-dimensional) metrics can be incorporated in modeling. It should be noted that this model formulation allows for efficient and parallelizable computation of simulation timesteps operating on data structures (profiles) that can be segmented both spatially and temporally, i.e. simulation resources are modeled independently and profiles can be defined independent of simulations. It should also be noted that even with well defined application and resource profiles, exact simulation of computational throughput is difficult to achieve due to variations in computation

behavior, data dependencies, resource contention, etc. The aim of the framework here is to provide a mechanism for experimentation, where behavior models can be iteratively refined for increased precision.

5 CONCLUSIONS

In this paper we discuss simulation of application and resource behavior in distributed computing environments. We note a current lack of simulation toolkits that encompass the dynamic behavior and resource heterogeneity of such environments, and propose a simulation model for combined discrete-time simulation of resources and discrete-event simulation of virtual infrastructures. In a brief performance evaluation we demonstrate that the proposed approach is scalable and parallelizable, and discuss how the formulation of (application and resource behavior) profiles capture modeling of resource heterogeneity, variability, and volatility.

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