International Journal of Mathematics, Statistics, and Computer Science
Vol. 3
ISSN: 2704-1077 eISSN 2704-1069, DOI: 10.59543/ijmscs.v3i.14191

Towards Accurate Energy Measurement Simulations in Cloud Computing Environments

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Received 19.04.2025, Revised 29.05.2025, Accepted 04.06.2025

ABSTRACT: Cloud computing has become an essential part of modern IT infrastructure, providing scalable and ondemand resources to users. As the demand for cloud services continues to grow, researchers and practitioners are facing the challange of optimizing energy consumption of data centers. Simulation tools are crucial in this endeavor, enabling a thorough understanding of these dynamic environments. In this paper, we underline the importance of realistic simulation in cloud environments, focusing on the energy consumption measurements accuracy from various resources using real world data. To address this, we integrate multiple energy metrics to enhance the replication of real-life scenarios. Our study highlights the need for advanced simulation tools for supporting energy dynamics of cloud environments.
Keywords: Cloud Computing, Simulation accuracy, Energy Consumption, Workload simulation, PlanetLab Workload.

1. INTRODUCTION

Cloud data centers play a pivotal role in modern computing, offering scalable and efficient platforms for today’s applications. Realistic simulation of data center components is important for understanding data center performance, resource utilization, and environmental concerns such as energy consumption requires realistic simulation of data center components [1][2]. Precise energy measurement necessitates a comprehensive energy model integrating both server and network resource usage [3]. For instance, modeling dynamic power consumption of servers based on their utilization levels and static power draw is necessary to capture the complexities of energy demand in data center. Moreover, capturing workload fluctuations and their effect on energy consumption are vital for a realistic simulation [4]. A robust energy model must consider workload fluctuations of data center operations, enabling simulations to replicate real-world situations where energy consumption is influenced by both the type and intensity of the workload [5]. To improve simulation accuracy, researchers often include trace-based workloads, where the parameters and the details of the workload are extracted from real-world data [6][7]. Empirical studies have shown that using real-world data traces is essential for enhancing simulation fidelity[8]. For instance, Alshammari et al. [9] observed that using simplified models in many simulators can often yield inaccurate energy behavior representations. Also, Da Silva et al. [10] highlighted that using real data improves cloud simulation and energy consumption accuracy by providing accurate profiles of power and energy metrics, allowing for better modeling of resource utilization. Similarily, Cesario et al. [11] showed that using real-world traces improves the accuracy of cloud simulation and energy consumption metrics, resulting in more effective virtual machine allocation and optimizing energy savings. Moreover, regularly updating simulation models with real data helps to minimize the difference between simulated and actual performance. The integration of the algorithm proposed by Beloglazov and Buyya [12] and the utilization of PlanetLab [13] experiment within CloudSim [14] have collectively established a standard benchmark in the field. This integration has sparked a trend where researchers, introducing new algorithms for the Virtual Machine (VM) consolidation problem, often use the algorithm by [12] as a benchmark for comparison, highlighting improvements through the PlanetLab experiment. While CloudSim offers valuable features for calculating energy consumption and modeling the state of data center components, critiques regarding its I/O processing model [15], communication models [16], and the inaccuracy of power calculation [17] have prompted a reevaluation of simulation frameworks. A more comprehensive simulation tool should allow for a detailed modeling of data center components and their state transitions to better reflect the dynamic nature of data center operations[18][19]. The representation of energy consumption from different states of Physical Machines (PMs) and VMs is crucial for accurate energy modeling. It can lead to inaccuracies in the simulation results [20]. SCORE (Simulator for Cloud Optimization of Resources and Energy Consumption) [21] is a cloud computing simulator designed to simulate cloud environments with a specific focus on optimizing resource utilization and minimizing energy consumption. While SCORE seeks to deliver a realistic simulation of heterogeneous data centers throgh providing parallel scheduling and energy-efficient models for the execution of synthetic workloads, it doesn't provide detailed networking models. In addition, SCORE doesn't endorse VM migration policies, which are important for modeling real-life scenarios in cloud systems. In real-world data centers, networking and VM migration play a crucial role in overall performance, and the detailed simulation of network-related aspects is limited in SCORE. DISSECT-CF [22] (DIScrete event baSed Energy Consumption simulaTor for Clouds and Federations) is a powerful simulation framework that provides ability to realistically model energy consumption. The simulator integrates sophisticated energy consumption models considering the intricacies of underlying infrastructure, including servers, networking equipment, and storage components. This allows researchers to gain insights into the energy usage patterns of cloud environments. DISSECT-CF produces highly accurate simulation results in terms of finishing time and energy consumption. The reported error of just around 1% in most cases indicates a high level of precision in capturing the behavior of cloud systems [23].

The ability of DISSECT-CF to deliver results much faster than CloudSim enhances its practical utility for researchers conducting extensive simulations. Based on the above discussion, we decided to use the DISSECT-CF simulator to produce a more realistic simulation of the PlanetLab workload trace. Table I shows a comparison of the cloud Simulators based on features they support.

Table 1. Features comparison of cloud simulators

Features	*CloudSim*	*SCORE*	*DISSECT-CF*
Communication model	limited	No	Full
PM/VM model	PM and VM	Only PM	PM and VM
Resource scheduling model	CPU and Network	CPU, Network, and Storage	CPU, Network, and Storage
Migration Policy	√	-	√
Distributed Architecture	-	√	-
Network Model	√	-	√

In our previous work [24], we have implemented a new trace loading mechanism in DISSECT-CF simulator in order to load PlanetLab workload trace and generate jobs that will be executed by the VMs based on their execution time. In this paper, we emphasize the significance of realistic simulation across various dimensions such as CPU, storage, and bandwidth, highlighting their direct impacts on energy consumption. Additionally, we present our insights into energy modeling within CloudSim and DISSECT-CF, demonstrating that DISSECT-CF yields more accurate and realistic energy calculations. The remainder of this work is structured as follows: section 2 provides an overview of PlanetLab experiments in CloudSim including our observation on some unrealistic behaviors. In section 3, we elaborate on our experimentation and re-implementation process aimed at enhancing the realism of simulating PlanetLab workload traces and also presenting the results obtained concerning energy consumption and host utilization. Section 4 concludes the paper.

2. PLANETLAB WORKLOAD TRACE

PlanetLab serves as a global initiative dedicated to advancing research in distributed computing enabling researchers to test and evaluate new technologies with regard to networking and distributed systems. It operates multiple co-located yet isolated user tasks, referred to as slices, through virtualization [13]. The CoMon monitoring system, designed for collecting and processing data from PlanetLab nodes [25], gathered valuable information about the temporal evolution of resource requirements for user's slices, from approximately 800 nodes over several years.

The only available remnants are the data of CPU usage spanning ten days and approximately thousand VMs, preserved in the planetlab workload folder of CloudSim. Beloglazov and Buyya [12] focused their experiments on CPU load, resulting in the retention of solely CPU load. These data are stored in uncomplicated text files, each representing a single VM for a day. Each line within the file corresponds to a distinct measurement, indicating the CPU load as a percentage of the requested resources. Typically, the CPU load was recorded at five minute intervals, leading to 288 lines per file representing the daily measurements for each VM. Table 2 shows the parameters used by [12] for evaluating their experiment.

Table 2. Parameters of planetlab experiment, as defined by [12]

PM Types	2
VM Types	4
CPU cores for each PM type	2
CPU cores for each VM type	1
CPU capacity for PMs(MIPS)	1860,2660
CPU capacity for VMs (MIPS)	2500, 2000, 1000, 500
RAM size (MB) for PMs	4000, 4000
RAM size (MB) for VMs	870, 1740,1740,613
Power Model for PMs	HP ProLiant ML110 G4, G5

VMs are initially created with requested resources adhering to the nominal values specified in the table. Consequently, these values govern the initial allocation of VMs to PMs. However, following the initial re-optimization phase, CPU values undergo modification in alignment with the PlanetLab trace, resulting in considerably reduced CPU loads. Additionally, the utilization values for RAM were not considered during this phase. This implies that, from first re-optimization onward, VMs occupy significantly fewer CPU and RAM resources compared to their initial placement. Figure 1 shows the power consumption characteristics for different CPU load intervals of HP ProLiant ML110 G4 and HP ProLiant ML110 G5 servers. For PlanetLab experiment in CloudSim, The inclination of power efficiency trajectory for G5 servers demonstrates a more favorable trend from 0% to 30%, compared to the range between 30% and 60%. This observed bias may result in suboptimal decisions by the algorithm [17]. To illustrate, in a scenario where the algorithm must choose between two G5 servers, one with a CPU load of 20% and another with 60%, for a VM with a CPU load corresponding to 10% of the total capacity of the PMs, the server with a CPU load of 20% will be chosen by the algorithm due to its higher power efficiency. However, this contradicts the VM consolidation consept, which advocates for consolidating the highest possible load onto already wellutilized PMs while attempting to free up lightly loaded PMs.

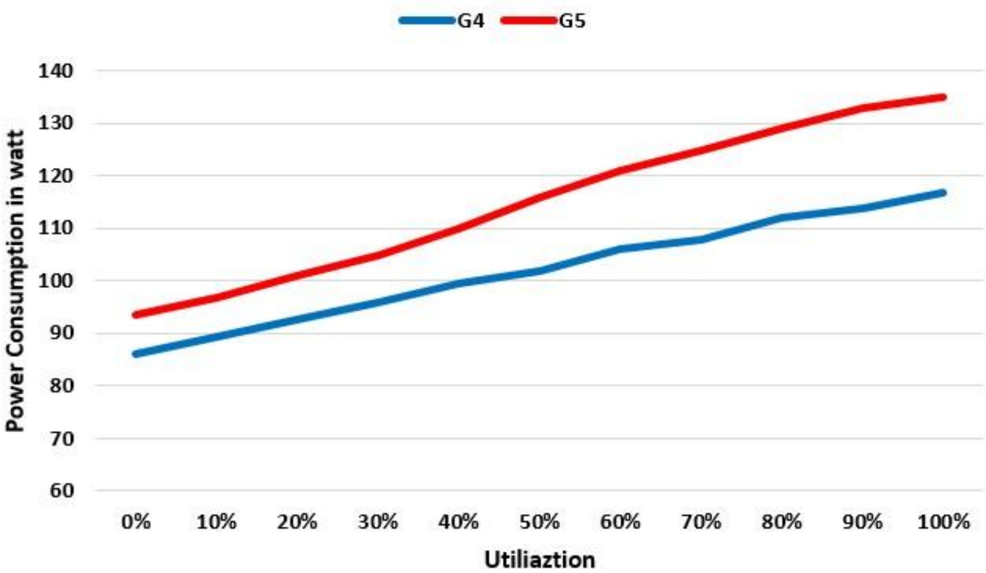

Figure 1. Power draw of different servers in watt at different utilization

In DISSECT-CF, the implementation of energy metering differs significantly from CloudSim. There is no straightforward method for querying the current PM's power draw. As a substitute, trying to imitiate the real life behavior, PMs can have a seperate meter for energy measurement that consistently monitors their energy usage. The power consumption of a PM over time is calculated based on its CPU capability during each time interval correlating with average power draw. Unlike CloudSim, the frequency of power calculations is independently determined for each energy meter object. The selection of the power calculation frequency represents a crucial tradeoff, as greater frequencies give more precision but also result in an increased execution time for the simulator.

3. EXPERIMENTAL RESULT

To enhance the realism of energy consumption modeling, we opted to replicate the PlanetLab experiment in DISSECT-CF simulator. This approach facilitates realistic simulations by incorporating diverse sources of energy consumption and allows for a comparative analysis with CloudSim. In our previous work[21], we introduced a trace loading mechanism in DISSECT-CF that generates authentic tasks based on PlanetLab workload traces, enabling jobs to effectively utilize VMs in the data center during simulation.

Moreover, we integrated two power models for G4 and G5 server types into DISSECT-CF. These models aim to simulate energy usage using diverse metrics such as CPU load, network bandwidth, and memory utilization. Additionally, we introduced power transition generators to simulate energy consumption across different states of both PMs and VMs, encompassing active, idle, sleep, and off states. For the initial allocation of VMs to PMs, we implemented a VM allocation policy designed to mirror CloudSim's VM allocation behavior. This policy considers realistic measurements, such as RAM and bandwidth utilization of the PMs, alongside current CPU utilization. To facilitate a direct comparison between the two simulators, we focused exclusively on the initial VM allocations without involving any VM migrations. Our primary objective was to assess differences in energy consumption, rather than delve into the decision-making processes related to VM migration by the VM scheduler. In our experiment, we implemented a data center consisting of 800 PMs, divided equally between G4 and G5 server types. Additionally, we utilized four types of VMs with varying resource specifications, as detailed in Table 2. And we utilized 10 days of data from the PlanetLab workload trace.

Figure 2 shows a comparison of energy consumption between CloudSim and DISSECT-CF utilizing an identical infrastructure setup. The increased energy consumption in DISSECTCF is attributed to the consideration of additional factors that impact energy measurements in real-life scenarios. This includes power consumption even when PMs are switched off, energy associated with PM state transitions (such as switching PMs on and off), as well as energy consumed by other resources like RAM and bandwidth, all of which CloudSim neglects.

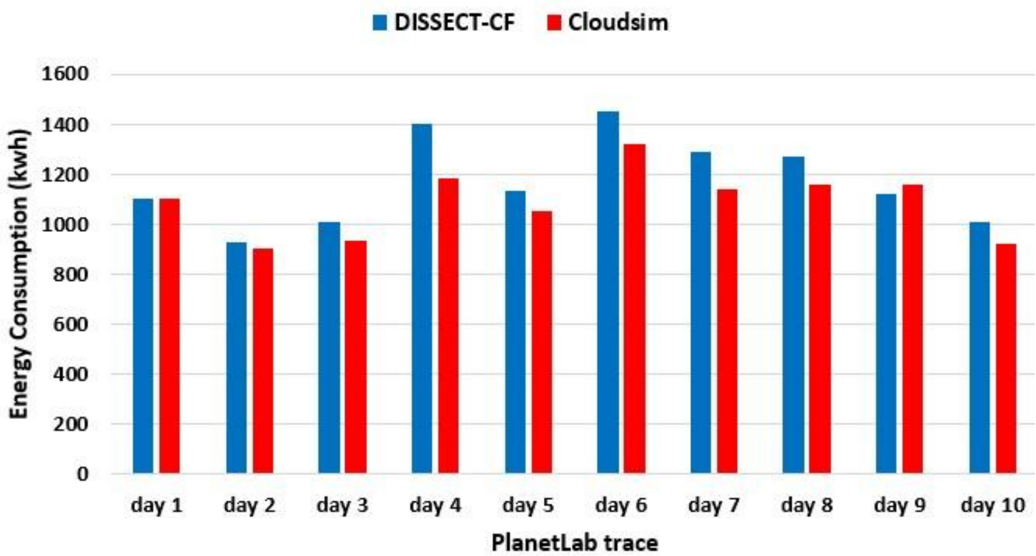

Figure 2. Energy consumption using PlanetLab workload

The initial calculation of power consumption in CloudSim occurs at time 0 in which VMs exhibit no CPU load, resulting in the assumption that each PM's power consumption is also 0 at this point. Consequently, the energy dissipation of the data center during the starting 5 minutes is inaccurately recorded as 0. In contrast, DISSECT-CF estimates energy consumption more accurately from the beginning, resulting in higher but more realistic recorded energy consumption values.

We also incorporated several power measurement sources when calculating energy waste in DISSECT-CF. This includes power consumption during state changes of PMs, such as from switching on to running, as well as energy consumed by other resources like network bandwidth, disk storage, and communication costs among VMs. These additions contribute to more realistic measurements of energy usage. Additionally, we observed that in the CloudSim power model, whenever the CPU utilization of a VM drops to zero, the energy consumption is recorded as zero for the next 5-minute interval. This behavior leads to inaccurate energy measurements. To ensure more precise energy consumption recording, we addressed this issue in our implementation of the Dissect-CF simulator. This adjustment is a key factor contributing to CloudSim's reporting of lower energy consumption. For a fair comparison between the two simulators, we aligned the VM allocation setup in both simulators to ensure identical VM-to-PM allocation mappings. Additionally, DISSECT-CF demonstrated significantly faster simulation times compared to CloudSim, as shown in Figure 3, making it feasible when simulating large scale cloud with varying demands.

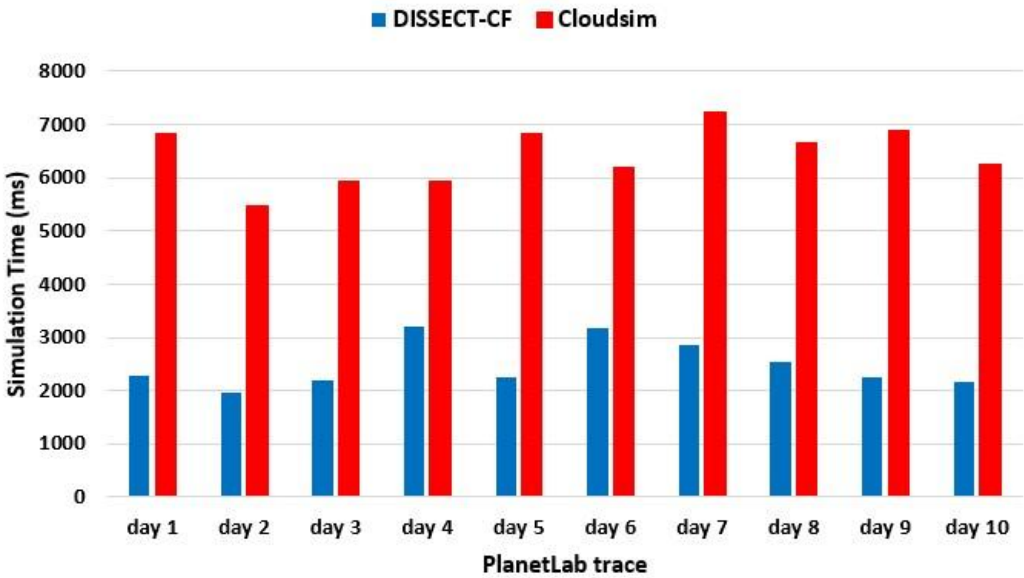

Figure 3. Simulation time for PlanetLab workload

Our evaluation of CloudSim and DISSECT-CF highlights the importance of simulation fidelity in modeling real-world energy behavior in cloud environments. Although CloudSim offers a fast and efficient environment for scenario testing, its simplified models, such assuming zero power draw during idle periods, can yield misleading conclusions for energy predictions.

On the other hand, DISSECT-CF provides additional power states for physical machines, such as idle, switching on and off, etc., adding more representations of energy consumption metrics. Furthermore, incorporating RAM, disk, and network resources into energy measurement enhances the simulation's realism, making it a powerful tool for developing energy-aware optimization research. Its characteristics are vital for algorithms that aim at balancing energy efficiency and system performance.

4. CONCLUSION

As distributed computing systems grow in complexity, simulation frameworks become essential for developing and assessing system performance. Due to the difficulty of precise power prediction in large infrastructures, accurate power modeling in large scale cloud environments remains a challenge. Thus, there is a growing need for simulation frameworks that adopt more advanced energy prediction mechanisms. In this paper, we highlighted the significance of cloud simulation tools in accurately modeling cloud environments. Our study showed that DISSECT-CF provide more accurate energy consumption insights, compared to Cloudsim, by incorporating various energy modeling for components like CPU, storage, and network. In future, we aim to include sophisticated VM Consolidation approaches and decision-making policies for better representation of real time consolidation scenarios. Finally, benchmarking simulations against real energy measurements could serve as a concrete empirical layer for assessing simulation realism.

Funding: This research received no external funding.
Conflict of interest: The authors declare no conflicts of interest.

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