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A Performance Optimization Model of Task Scheduling towards Green Cloud Computing

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Abstract: Cloud computing becomes a powerful trend in the development of ICT services. It allows dynamic resource scaling from infinite resource pool for supporting Cloud users. Such scenario leads to necessity of larger size of computing infrastructure and increases processing power. Demand on the cloud computing is continually growth that makes it changes to scope of green cloud computing. It aims to reduce energy consumption in Cloud computing while maintaining a better performance. However, there is lack of performance metric that analyzing trade-off between energy consumption and performance. Considering high volume of mixed users' requirements and diversity of services offered; an appropriate performance model for achieving better balance between Cloud performance and energy consumption is needed. In this work, we focus on green Cloud Computing through scheduling optimization model. Specifically, we investigate a relationship between performance metrics that chosen in scheduling approaches with energy consumption for energy efficiency. Through such relationship, we develop an energy-based performance model that provides a clear picture on parameter selection in scheduling for effective energy management. We believed that better understanding on how to model the scheduling performance will lead to green Cloud computing.

Keywords: green cloud; scheduling; energy efficiency; optimization model; energy management.

1. Introduction

Cloud computing is a state-of-the-art technology where it provides computing services i.e., IaaS, PaaS and SaaS to users [1, 2]. Basically, Cloud providers e.g., Amazon, Microsoft and Google provide their users with resource sharing model where resources (e.g., processors, storage) can be added and released easily either they are needed or otherwise. Particularly, large computing and storage infrastructure like Cloud needs more energy to generate sufficient electricity and cooling systems thus more expenses need to be invested. Furthermore, computer systems not only consuming vast amount of power also emit excessive heat; this often results in system unreliability and performance degradation. It has been reported in previous studies (e.g.,[3-5]) that system overheating causes system freeze and frequent system failures. According to the authors in [4] the highest energy cost of data centers are used to maintain the running servers. The servers need to be available and accessible throughout the year even though nobody is accessing them. Such situation incurs high cost in electric and cooling systems.

In order to sustain with good service reputation, the data centers needed to facilitate the processing and storage requirements for 24/7. The consequence of high resource availability in Cloud is not merely to financial expense but worse to environment through carbon footprint. There are more greenhouse gas (GHG) released in the atmosphere that leads to global warming, acid rain and smog [6]. Although there have been many research efforts to reduce the energy consumption in computing operation, there is still lack of a decision support system for choosing the right performance metric in dynamic computing environment. The large-scale distributed system like Cloud needs to support large number of users with diverse processing requirements. Meanwhile, the performance degradation at any stage of processing is unacceptable. It is a challenge to find the best trade-off between system performance and energy consumption in Cloud.

In task scheduling approach it mainly aims to maximize or at least sustain the system performance. Such scheduling approach able to promote better energy consumption by effectively scheduling users' requirements based on resource availability [7-10]. In the conventional scheduling optimization model, the performance parameters are usually specified as deterministic. However, in realistic energy management systems, many parameters are dealing with uncertain natures with multiple states and features. When it comes to green Cloud computing, several issues are need to take into account, for example, security, accuracy and energy. In respect of energy saving, there are few aspects that needed to be highlighted such as power management, virtualization, and cooling. Energy efficiency for Cloud computing involved several series of interaction and interdependent between relevant system components, processes and metrics. Hence, it is needed a clear guideline for assessing performance and energy efficacy of Cloud especially in its scheduling and provisioning activities.

In this paper we focus on efficient energy consumption that influenced by parameter selection in the scheduling approach. We develop optimization model for energy-based scheduling that aims to provide a guideline for analyzing the better trade-off between system performance and energy consumption in Cloud. We then investigate the relationship of performance metrics that chosen in the scheduling approach with energy consumption to facilitate green computing. It is wise to effectively manage energy consumption in Cloud computing; this would in turn be very beneficial cost of computation.

The reminder of this paper is organized as follows. A review of related work is presented in Section 2. In Section 3 we describe the parameter categories that chosen for efficient energy management. Section 4 details our performance model for energy efficiency. Experimental setting and results are presented in Section 5. Finally, conclusions are made in Section 6.

2. Literature Review

The energy management has inspired many researchers [3, 4, 11-15] to focus on green Cloud computing. The scope of energy assessment for modeling its performance should be stretched further incorporating parameter selection and energy model that being used. In [16], the authors emphasized resource utilization in their energy model. They utilized the virtualization as a core technology to contribute green IT because it able to share limited resources with varies workloads. The quantity of physical machines (PMs) can be reduced where processing is performed by virtual machines (VMs). VMs are very flexible that act as independent servers that maximized resources utilization while achieving energy efficiency. However, the selection of parameters in their performance model for energy efficiency is still an open issue. Some researchers focused on resource state in their energy models. According to the authors in [12], processors consumed approximately 32Watt when they are operated in idle mode that compared to storages merely used 6Watt. In peak processing mode the energy consumption of processors can be boosted up to more than 80Watt to 95Watt [17]. Energy efficient scheduling that proposed in [8] dynamically allocated users' tasks into processor to achieve better performance and minimize energy consumption. The system performance and energy consumption in their work is been measured throughout the task execution either during peak or idle state, then total energy consumption is recorded.

There are also some works that calculated the energy consumption through their modern scheduling approaches. Power-efficient scheduling in [7] assigned set of virtual machines (VMs) to physical machines (PMs) for data centers management. They used the consolidation fitness to determine the right VMs to replace PMs when existing PM is been switched off. However there is challenge to determine the most right VM due to unpredictable changes in the system workload. Power-aware mechanism in [18] is based on priority scheduling for efficient energy management. They adopted various heuristic for energy-aware scheduling algorithms that employed multi-objective function for diverse efficiency-performance tradeoffs. Their scheduling algorithms consist of three steps (i.e., job clustering, re-evaluating to give better scheduling alternatives and selecting the best schedule). They conducted the experiments in homogeneous environment that disguises Cloud computing environment. The existing researches that proposed energy efficient scheduling are able to reach appropriate balance between system performance and energy consumption. However, the dynamicity and heterogeneity on their computing environment are limited to some extent.

There are some researchers (e.g.,[4, 6, 19]) that highlighted the incorporation of low-energy computing nodes in heterogeneous distributed systems and able to achieve energy efficiency. Due to the scheduling approaches are subjected to system environment and scale, it required effective performance model for better evaluation on both performance and energy usage. However, there is lack of exclusive parameter selection strategy for energy management in order to balance between system performance and energy consumption. In Table I, we summarized the selection of performance metrics and system behaviors that used in those existing scheduling approaches to design energy model.

Table 1. Relationship between Scheduling Rule and Energy Model

No.	Scheduling Rule	Energy Model
1	Heuristic approach used for pre-scheduling processing. Such predictable rule satisfies energy saving where it consumed less processing time.	It considers busy and idle states of processing elements.
2	Threshold for processor, memory, disk and communication link in resource allocation. If the threshold chosen is too low it might reduces resource utilization while setting too high threshold leads to communication bottleneck.	It considers resource utilization and overhead in the system.
3	Migrating or remapping strategy in scheduling using a set of virtual machines (VMs).	Virtualization leads to energy efficiency.

3. Classification of Scheduling Parameters

The existing scheduling approaches (e.g.,[3, 4, 7, 20]) analyzed the performance of their energy management system through various scheduling algorithms. They have chosen several types of parameters such as time-based perspective, utilization and overhead.

3.1. Time-based Metrics

Time-based metric is one of the most popular parameters that chosen for focusing green Cloud. Such parameter used to measure the effectiveness of scheduling decision for uncertain, dynamic and large-scale environment. The time-based metrics, for example, execution time, waiting time and response time is designed to monitor and manage queuing problems in scheduling. The major problem in scheduling is to allocate various users' jobs to be mapped and executed by the right resources. Due to the scheduler needs to get information from users and resources, the scheduling decisions are most of the time consumed more processing energy compared than storage. The resources need to be available to perform the job execution at most of the time. Therefore, in order to improve the execution time for minimizing energy consumption we need to take into account the optimization technique in designing scheduling approach.

Furthermore, the issue on suitable queue length comes into a picture when the total waiting time of jobs leads for high energy consumption. Note that the determination of queue size is significantly related to the scale of computing system. Specifically, the queue size contributes for better job waiting time that it relates to buffer management. The suitable size of queue needs to be identified to reduce data access time in the buffer. We do not want to power the entire memory module in lengthy time only for data accessing operation. Hence, the effective scheduling approach for dynamic environment required to define the (most) suitable queue length for reducing power consumption.

3.2 Utilization

There are scheduling approaches that calculate the energy consumption based on computing resources' busy and idle states. In particular, the resources that have high busy time means the system utilization is improved. Meanwhile the system is considered has low utilization when there are many resources that idle in a given observation time. However, from energy management perspective, high utilization may leads to large energy consumption. The resource that has high utilization certainly consumed high processing energy in order to complete the task execution. It is more crucial in the idle state of resources. There is huge percentage of power consumption (i.e., for electricity and cooling systems) to facilitate the running resources. The idle resources need to be available even though there is no processing happen in their space. Resource utilization only 53% of total energy consumed in data centers [21]. Therefore, the best solution is to effectively manage resource utilization for energy efficiency. There is a big role for the scheduler to monitor resource utilization in dynamic environment.

3.3. Overhead

The storage and processing resources in Cloud must be highly available that it reflects Quality of Service (QoS). It included the ability of Cloud to adapt with unexpected failures, e.g., storage overloaded, traffic congestion and performance fluctuation. Such scenarios needed extra time for the Cloud providers to solve and fix without notify the users. Some strategies used replication of objects and services, and using redundant processing and communication mechanisms to solve the unexpected failure. In order to implement these strategies they need more than one communication paths that used for disseminating the same information, and several processing elements for processing the same action. In scheduling approach, we need to design extra procedure or policy to manage such unexpected failure and implement reserve strategy. It explicitly incurred extra communication and processing overheads in the systems. For the sake of energy efficiency, overhead should be minimized while maintaining system performance. Hence, tunable parameters in experimental setting are significant to thoroughly identify the system behavior/action in order to achieving the target results (better trade-off).

4. Optimization Stages for Energy Efficiency

There are various performance models that adopted in scheduling approach for energy efficiency (e.g., [3, 4, 7, 9, 15]). In this work, we specifically divide our optimization model for energy-based scheduling into three stages; (i) identifying, (ii) formulating, and (iii) modifying.

4.1 Identifying Stage

There are several energy issues such as energy waste, inaccurate energy measurement etc. that identified by existing researchers (e.g. [6, 14, 22]). The percentage of energy consumption in task scheduling is normally differs from one scheduler to another as there are other factors that contribute to such amount [16]. Some scheduling approaches e.g., heuristic and game-theory might improve the system utilization but energy efficiency. It is because energy management not entirely dependent on the selected scheduling approaches. Furthermore, the system goal generally aims to increase the system performance while minimizing the energy consumption. These maximize and minimize objectives need to be carefully designed in order to avoid nastiest unbalance outcome.

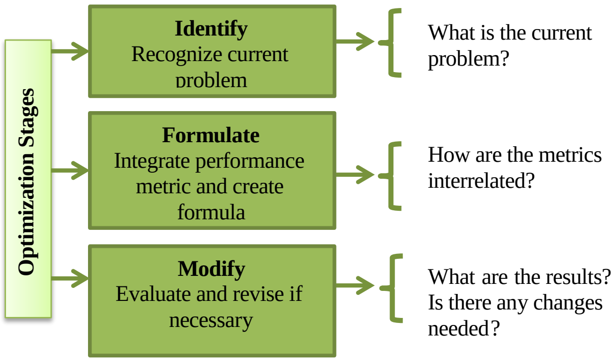

Figure 1. Energy-based Performance Model

In our optimization model, the identifying stage focuses on analyzing current energy-performance problem in the system. Initially, there is required to thoroughly understand the relationship between the system performance and energy consumption in the current computing system. Such review is important to determine a pattern on how the energy consumption crosses or touches the system performance during the execution process. The investigation on energy consumption in large-scale data center can be analyzed through its operational infrastructure. Such infrastructure can be classified based on power usage for physical equipment and processing condition. It leads to two different measurements of energy efficiency are; power usage effectiveness (PUE) and data center effectiveness (DCE) [16]. For PUE measurement, it concerns on total power used for IT equipment such as server, routers and cabling. Meanwhile DCE is calculated through the resource management strategy (i.e., scheduling, load balancing and security) that been applied in the server room or data center for complying the users' requirements. Both PUE and DCE are inter-related to each other for supporting computing operations.

Note that the high performance scheduler consumes high processing power at its peak processing time. This means to meet the users' requirements for task scheduling purposes, hence increases the energy consumption exponentially. At other scenario, there is IT equipment in data center that used electricity to make them available 24/7 to facilitate processing purposes. Even though Cloud utilizes the virtualization technology, it still relies on the physical computing equipment at its end support. For monitoring energy consumption from IT equipment perspectives, the energy distribution must be accurately measured. It is due to the usage of those equipment contributes to electricity bill that basically relates to operational and maintenance costs. For example, the server rooms or data centers needed of mechanical and electrical (M&E) infrastructure, also ventilating or cooling infrastructure for supporting the operational in the room. Nowadays, the actual cost for managing the IT equipment either in server room or laboratory has become big issue in organization.

The performance model then should be focusing on how to utilize the usage of IT equipment hence the energy distribution can be optimally consumed. Several strategies such as scheduling, load balancing and authorization are needed to be highlighted in order to optimally manage and utilize the energy distribution. In this work, we proposed task scheduling strategy that acts as mediator in order to monitor system performance and processing power in a same time. The scheduler is designed to be capable for analyzing the effectiveness of the scheduling processes by identifying which scheduling pattern leads to energy waste. In priori, the scheduler should be expected to produce a scheduling pattern that gives better performance without enlarge energy consumed.

4.2 Formulating Stage

Cloud computing enables its services (i.e., IaaS, PaaS, SaaS) for various users at anywhere for anytime. It required to provide reliable in both computation and communication activities. In order to sustain the performance, thorough investigation of resource management specifically task scheduling is required. Note that the system performances are much influenced by the feature of system and characteristics of the users. Therefore, it is important to formulate the performance parameters in assessment method that based on system environment and its scale. In this stage, we gather relative performance metrics to create formula for assessing energy efficiency. Such criteria can be defined according to several levels that represent their complexity in communication and processing activities.

In this work, we highlight three level of system complexities; (i) homogenous/heterogeneous, (ii) static/dynamic and (iii) local/centralized/distributed. High in complexity means huge amount of energy consumption that consumed for task scheduling decisions. For example, the system is considered consumed large amount of processing energy when there is a huge number of incoming tasks to be scheduled. Also, the data center is needed a large number of processing elements (PE) to offer high availability in processing. In some cases, the small number of PE is yet consumed large percentage of energy. It happens when the PE is operated for 24/7 and it needed very cold room to control the heat releases. Note that excessive heat emitted by these PE causes notable power consumption for cooling them. In addition, the energy consumption is proportional to the users' requirements. The resources operated in extensive processing time if there is huge number of workload in the system. Such situation leads to increase the energy usage in the whole system operation.

In response to the system and user criteria, selection of performance metric to achieve better trade-off between performance and energy consumption is a huge challenge. The users in large-scale computing system normally demand for varies of processing requirements. Hence, the system performance needed to fulfill the users' requirements in order to sustain the system's reputation. This is very important in Cloud because there are many Cloud providers that competing each other to provide better performance. Therefore, the performance metrics to evaluate energy consumption should be fragmented of a total/average of the system performance. The system performance might be reduced because its portion needs to embrace the energy consumed.

In response to the collection of performance metrics, we then raise issue on how to integrate each metric for energy efficiency. Basically, the metrics aim for better scheduling decisions that leads to improve the system performance. In response to energy efficiency, the design of scheduling approach should able to monitor both performance and energy consumption for a given time duration. It is wised to capture energy consumption for a specific time duration that can be based on incoming workload while calculating the average of the execution time. It is because; by frequently measuring the energy consumption it implicitly increased a percentage of power usage. The right proportional of the system performance e.g., total execution time to measure the energy consumption must be significantly concerned.

For instances, the performance metric in Cloud data center is measured by processing overhead as follows.

$$\min_{\text{overhead}} = \left(\frac{\sum idle_{time} + \sum busy_{time}}{total\ number\ of\ task} \right) \tag{1}$$

The total energy consumption in the system can be calculated as given:

$$total\ energy\ consumption = \frac{\sum total\ overhead}{simulation\ time} \tag{2}$$

; assumed that the energy consumption is measured through simulation program. In such example, the total number of incoming task is recorded within the scheduling process that used to calculate the overhead. Meanwhile, the energy consumption is measured for entire simulation program. In some scheduling approaches (e.g.,[9, 21]), they used fix power consumption (in Watt) that identified at busy and idle states of processing element for calculating energy consumption.

Table 2. Suggestion Metrics

No.	Evaluation Scope	Metrics
1	Hardware measurement	Real-time voltage and current, processing state/frequency.
2	Data Center	Time-based performance, utilization, processing overhead.
3	Mobile Cloud Computing	Communication overhead (transaction delay and traffic congestion).

In this work, we also express some metric suggestion for energy efficiency that can be chosen based on a given evaluation scope (Table 2). From Table 2, it is merely that item number 2 and 3 are related to scheduling approach where it can be formulated to maintain the system performance while monitoring the energy consumed. Due to the large scale constitution of Cloud environments, such parameter selection is considered to be unbounded and still an open issue.

4.3 Modifying Stage

Energy-based scheduling approach aims to schedule users' tasks to be run on the computer systems that consumed low energy consumption. It means that the computer system can tune the processing states to adapt with system changes while reducing the system energy consumption. In response to this, the computer system needs to collect run-time information of applications, monitor the processing energy consumption states, notify about states changes and compute energy-based scheduling decisions. Through the monitoring process, the system administrator is able to identify the processing activities that consumed large amount of energy. Then, it can perform modification in the scheduling policy in order to balance between the system performance and energy consumption. Such modification procedure might be involves several alteration techniques (i.e., fading, chaining, looping etc.).

The most significant step in this modification stage is trial-and-error process. Due to task scheduling in dynamic computing system is known as nondeterministic polynomial time (NP) problem, in this work we suggest to use the concept of *generate-and-test* which is one of heuristic methods in solving NP issue. The *generate-and-test* process will be investigated on how the systems and applications respond to the processing state changes. We then adjust the performance metrics that fit to the target goal (better trade-off between performance and energy consumption).

In some cases, the modifying stage implicitly used to track any misidentify in the previous stages. The dynamic scheduling involved many challenge issues such as high complexity, huge overhead and performance degradation. The identification on the right system environment with the suitable performance metrics is needed to be thoroughly analyzed. The suitability in both criteria for optimizing the system can be solved during modification process. For example, the waiting time might be not the right performance metric used for calculating energy consumption in the scheduler queue for public Cloud. It is due to the public Cloud is much expected by the large-scale number of workload that coming 24/7 that results extensive waiting time. Hence, in modification stage, the Cloud provider can change the performance metric by combining both waiting time and processing overhead in order to measure the energy consumption. The Cloud provider can design adaptive backup and maintenance activities in scheduling approach to reduce processing power that consumed for such activities.

5. Experimental Results

In this section, we experimentally evaluate several task scheduling approaches through our proposed optimization model for energy management. The scheduling approaches are chosen based on the common scheduling algorithms e.g., FCFS, Shortest-Job-First (preemptive), Shortest-Job-First (non-preemptive) and random. The main extension made to these algorithms is the incorporation of our optimization model. It means that the scheduler in each algorithm will complied with the all three stages in our optimization model. In order to evaluate the effectiveness of our performance optimization model, we compared with the scheduling approach that does not support the optimization stages (named *non-opt scheduler*).

In our experiments, there are two different Cloud components are storage and compute Clouds. In Cloud storage it involved data and information services. Each compute Cloud contains a varying number of compute resources ranging from 5 to 8 similar to that used in [8]. Both Cloud components are attached with a Cloud broker or so-called as a scheduler, in our study. There are several users that regularly request and get response from the Cloud. For this work, in every experiment there is considered 20 users with random task arrivals.

Results in Fig. 3 clearly demonstrate the competent capability of *opt-scheduler*. While *SJF-nonpreemp* showed appealing results, it is observed that average processing overhead in *opt-scheduler* is about 70% better compared to *non-opt scheduler*. Meanwhile, Fig. 4 shows a reduction of more than 50% on average in energy consumption. Note that energy consumption with *opt-scheduler* exhibits better results in all scheduling algorithm and indicates that the differences is relatively small. In overall, the *opt-scheduler* able to deliver low energy consumption and better processing overhead in several scheduling policies. Therefore, it is significant in aggregating three optimization stages (Section 4) to strive for better performance and energy consumed.

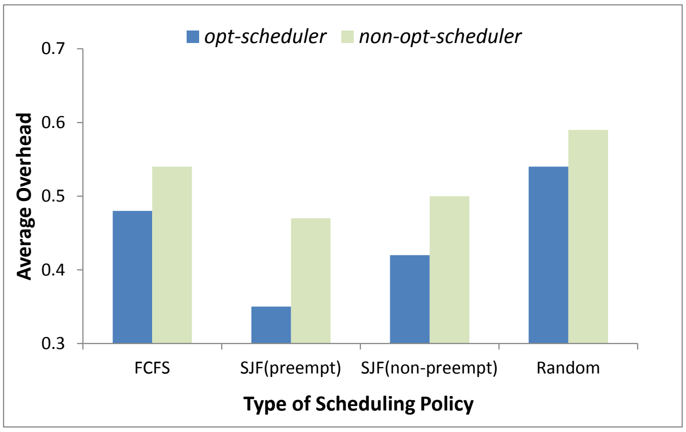

Figure 2: Average processing overhead for different scheduling policies

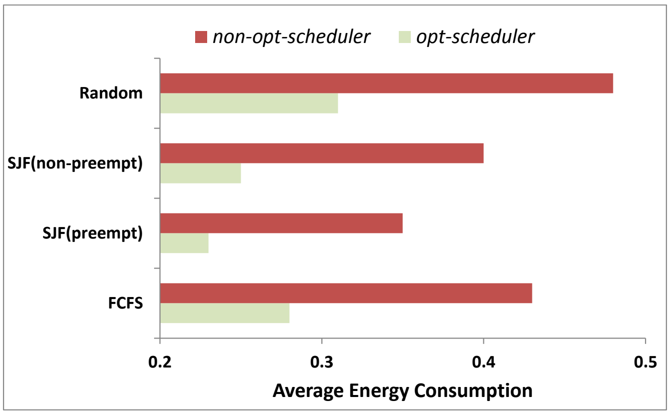

Figure 3: Average energy consumption for different scheduling policies

6. Conclusion

The concept of green computing has begun to spread in the past few years and still gaining its popularity. It is due to its significant performance, environmental and economic implications. In this paper, we analyze relationship between the parameter selection in scheduling approach and energy consumption that brings to energy efficiency. Specifically, we develop the performance model for optimizing the task scheduling where the energy efficiency becomes the next goal. Note that, the (near) optimal scheduling for energy efficiency is still an open issue. Hence, there is a lot of potential for more research on its performance model and design. Optimistically, Cloud able to achieve better trade-off between performance and energy consumption when there is clear guideline for designing the energy-based performance model.

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