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Machine Learning Based Intelligent Management System for Energy Storage Using Computing Application

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Abstract

INTRODUCTION: Cloud computing, a still emerging technology, allows customers to pay for services based on usage. It provides internet-based services, whilst virtualization optimizes a PC's available resources.
OBJECTIVES: The foundation of cloud computing is the data center, comprising networked computers, cables, electricity components, and various other elements that host and store corporate data. In cloud data centers, high performance has always been a critical concern, but this often comes at the cost of increased energy consumption.
METHODS: The most problematic factor is reducing power consumption while maintaining service quality and performance to balance system efficiency and energy use. Our proposed approach requires a comprehensive understanding of energy usage patterns within the cloud environment.
RESULTS: We examined power consumption trends to demonstrate that with the application of the right optimization principles based on energy consumption models, significant energy savings can be made in cloud data centers. During the prediction phase, tablet optimization, with its 97 % accuracy rate, enables more accurate future cost forecasts.
CONCLUSION: Energy consumption is a major concern for cloud data centers. To handle incoming requests with the fewest resources possible, given the increasing demand and widespread adoption of cloud computing, it is essential to maintain effective and efficient data center strategies.

Keywords: Cloud computing, Machine Learning, Physical Machine.

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1. Introduction

Large-scale data centers must be created to meet the ongoing growth in demand for computer resources. These data centers consume a substantial amount of electrical power to deliver essential services to cloud clients, which as an unintended consequence, increases carbon dioxide (CO_2) emissions as well as operational costs. According to research, data centers use around 1.3% of the world's total electrical supply, and by 2020 this percentage is predicted to increase to around 8 % [1]. As a result, CO_2 levels are rapidly rising and pose a significant threat to the environment.

The excessive energy consumption is not primarily due to the extensive use of computer resources, but rather the wasteful and inefficient usage of these resources. Unfortunately, hosts consume a significant amount of power even when there is only minimal activity. Most hosts operate at 10 to 50 % of their maximum capacity, wasting energy during periods of low resource utilisation, according to data on host resource consumption gathered over a six-month period from more than 5,000 production hosts [2, 3]. Another issue is related to the limited dynamic power range of servers; even when completely idle, they still require approximately 70% of their peak power [4]. As a result, allowing servers to remain underused lead to extremely wasteful energy use.

A significant challenge lies in identifying a way to lower data energy use while preserving the cloud provider's service level agreements. Virtualization can help address this high energy consumption [5, 6]. By using virtualization technology, VM users can customize their runtime resources to meet their specific needs by gaining administrative access to the guest operating system. These virtual machines are capable of running many applications simultaneously [7, 8].

A key strategy for optimizing the utilization of computer resources in data centers is dynamic virtual machine (VM) consolidation. By employing live migration to reassign the VMs according to current resource requirements, the amount of idle hosts is minimized [9, 10].

These idle hosts are quickly switched into power conservation mode to reduce static power and overall energy usage. When workload demand increases, hosts can be restarted. The two major goals of this method are to prevent Service Level Agreement (SLA) breaches and to use power more efficiently [11].

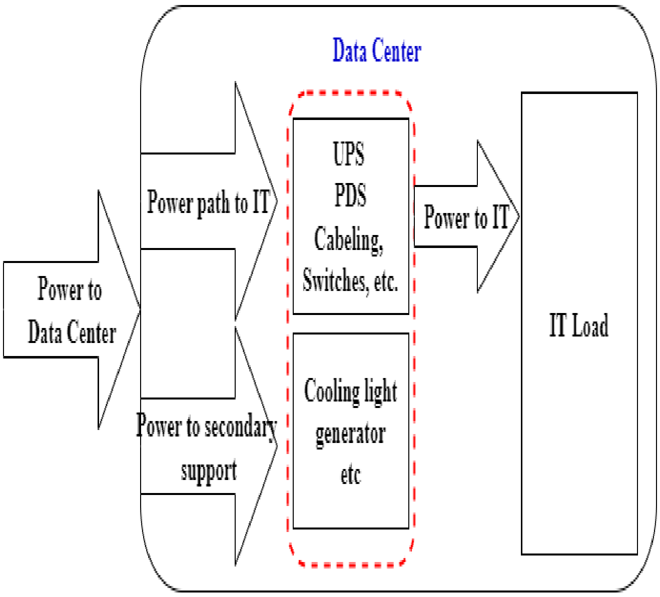

Figure 1. Power flow for the Data Center

In data centers, virtualization is a crucial technique because it enables users to share resources by utilizing virtual machines (VMs). Each VM is used separately to run customer applications or packages, addressing storage capacity, primary memory and other more specific needs [12, 13]. These changes are critical in making significant improvements to cloud computing performance.

When a virtual device's required resources are unavailable on the physical machine, VM migration occurs, resulting in physical machine (PM) consolidation. To satisfy the VM requirement, the VM is transferred to another physical machine [14].

Before VM migration, this recommended approach predicts the power consumption of each VM. This allows VMs to manage operations more effectively [15, 16] and offers clients a more reliable service.

Energy savings can be achieved by forecasting power utilization using various machine learning techniques. A primarily machine learning-based approach is used to predict the energy consumption of virtual machines, optimize cloud computing infrastructure, and enhance services. The power consumption of virtual machines is also predicted before they are allocated to physical machines [17].

To analyse this thoroughly, we reflected upon earlier studies on workload prediction and energy consumption in cloud computing environments within a literature review. From this we finalized a proposed system for energy consumption; one based on machine learning techniques alone. The overall performance assessment of the suggested technique is demonstrated in section 4, and the conclusion and feedback supplied in section 5.

2. Literature Review

One of the most effective methods for predicting future trends is to establish a robust foundation in energy management for the cloud, including built-in CPU utilization forecasting, resource usage forecasting, and overall management. This approach helps reduce operational costs for cloud provider providers. Various energy-aware methods and power conservation strategies for data centers were investigated.

To enhance the performance of complex systems, future energy costs are estimated using power consumption prediction. One study evaluated overcrowded servers with restructuring based on CPU consumption, using the interquartile range, which is automatically adjusted [18].

Another focus was on using autoregressive prediction to forecast network demand [19]. The sample sizes used for identifying relationships among characteristics were smaller in this approach. To calculate VM energy usage, [20] proposed a tree regression (TR)- based model using integrated password-validation and a black box approach.

The black box method was used to gain more insight into server and VM functionalities. A variety of statistical data was used for the prediction model. By scaling both vertically and horizontally, an autoscaling method was employed to reduce the operational costs of virtual resources [21].

A self-adaptive differential evolution method was developed to predict the workload required by the cloud data center [22], utilising data from Nasa and the University of Saskatchewan. The authors fine-tuned the fitness function, mutation and crossover processes, concluding that this technique outperformed others such as particle swarm optimization (PSO), genetic algorithms (GAs), and several other methods [23-27].

3. Proposed Methodology

The suggested approach introduces a new technique for maintaining cloud computing power efficiency by shifting the busiest virtual machines to the least loaded active system, whilst still preserving overall system performance. That is carried out by performing a live migration of the virtual machines, ensuring that no running applications are interrupted.

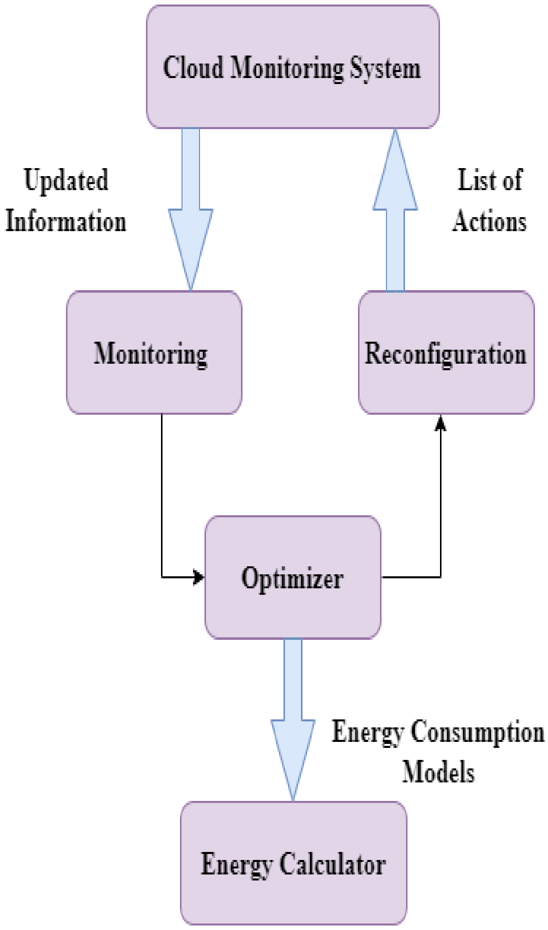

Figure 2. Energy consumption architecture

The proposed solution introduces a novel technique for enhancing resource utilization using a tablet optimization approach to improve energy efficiency in cloud data centers. The energy-saving system design, incorporating optimization, reconfiguration and monitoring, is depicted in figure 2. The entire condition of the cloud environment is automatically inspected.

A comprehensive evaluation of the current state of cloud environments and data center resources, including key energy consumption features and interconnections, was another significant contribution of the overall picture.

To identify software applications which could be substituted and locate service-allocated settings that enable energy savings, the optimization module automatically assesses conditions.

The loop is completed via a series of operations on the cloud environment to adjust and regulate energy- setup allocation after determining an optimal configuration.

The monitoring and reconfiguration modules interact with the cloud environment monitoring framework to fulfill

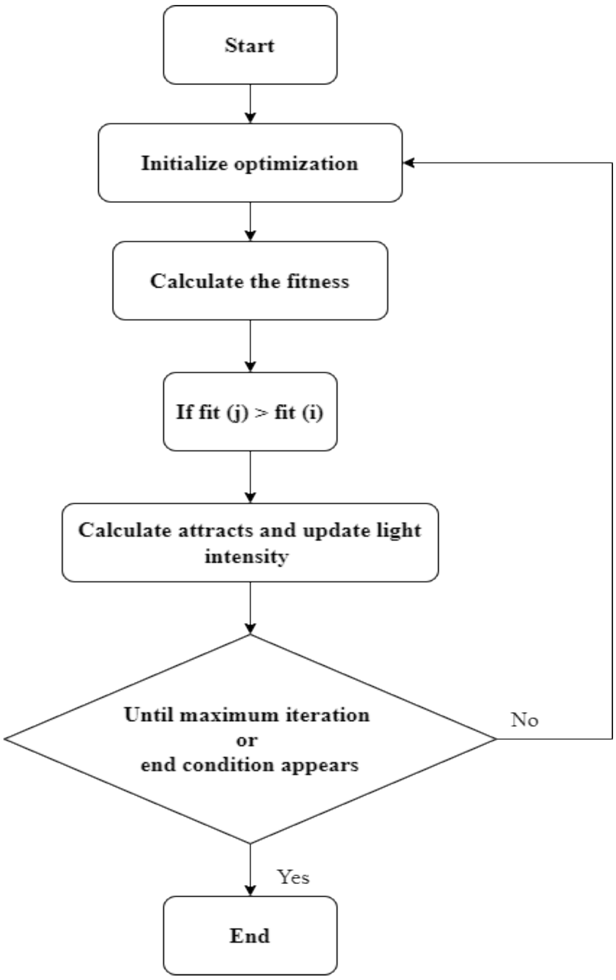

Figure 3. Flowchart of tablet optimization algorithm with proposed methodology

their required tasks. This is primarily based on the estimated energy usage of the power calculator module, where the optimization module ranks necessary target configurations.

To achieve this, energy-saving policies are followed whilst adhering to any existing constraints. This module can predict the energy consumption of a cloud environment following a potential reconfiguration preference, which is crucial for selecting the best energy-saving alternatives.

We fed the training data into the prediction model and were able to forecast power usage based upon meteorological data. Using test data, the prediction model was then validated by comparing the estimated consumption to the actual energy used and then making an evaluation (test sequence).

The amount of training data applied exceeded the total available sensor records, and the remaining sensor data was used as a test sequence to examine and compare the predicted values to the measured values.

4. Result & Discussion

This section offers an in-depth evaluation of each scenario as well as the results of testing. The experimental assessment was conducted with the use of the Cloud Sim toolkit, which is a significantly, well-preferred and widely accepted framework for simulating and reproducing local computing environments in the cloud [29]. Cloud Sim toolkit can mirror the operation of cloud components such as data centers, virtual machines, and resource provisioning constraints, as well as their behaviour [30]. For the test, we selected a sample size of 100 tasks, initially distributed across 5 virtual machines.

Table 1. Computed results for Tablet Optimization Algorithm

S. NO	Time	Time	Time	Utilization	Assumption
T0	0	10	10	28	28.5
T1	2	4	3	14	15.1
T2	9	6	3	43	44.5
T3	17	3	16	54	55.7
T4	23	6	17	83	85.1

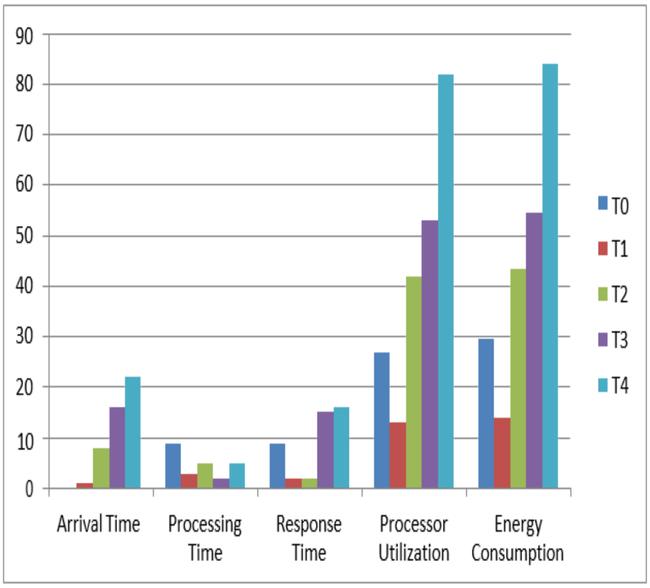

Figure 4. Quantitative Analysis

The testing was further validated by using additional jobs and virtual machines. The research project was evaluated by comparing all documented results. The utilization instances of each running process were modified using the energy calculation described above, providing energy consumption parameters for both the PSO and tablet optimization algorithms. The obtained data was then categorized and compared.

5. Conclusion

Energy use is a significant issue for cloud data facilities. To handle incoming requests with the most minimal resources possible, given the increasing demand and broad adoption of cloud computing, it is now more vital than ever to maintain efficient and effective - and as a consequence "green" - data center strategies. This is a prominent focus for researchers at this time which deserves further investigation. In this paper, we have promoted load balancing using newer methods, such as PSO or tablet optimization. Our interest was initially piqued by a study which implemented load balancing with PSO, and as a result we applied the same concept using tablet optimization. To evaluate the effectiveness of our proposed approach, we evaluated the energy used, with analyses definitively displaying that the tablet optimization technique is more successful at maximizing energy efficiency, and thus displays the most promise for the effective resource strategy in cloud computing environments.

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