A Systematic Review on Energy Efficient Approaches for Cloud Computing

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Abstract
In cloud computing, the saving of energy is major issue in data cetres. Furthermore, the establishment of large-scale. Cloud data centers due to the fast growth of utility-based IT services made the energy usage of data centers a concern. Cloud data centers use load balancing algorithms to allocate their physical resources (CPU, memory, hard disk, network bandwidth) efficiently on demand and hence optimize their energy consumption. In the load balancing process, some Virtual Machines (VMs) are selected from over- or underutilized physical hosts and these VMs are migrated, while live and running, to other hosts. In cloud computing various energy saving approaches has been implemented but in this we present the review of literature on the implemented approaches of energy saving. In this we also discuss the various energy efficient approaches of cloud computing.

Keywords: Cloud, Data centers, Energy, Literature, Virtual Machine.

Introduction

Cloud Computing is an emerging and promising paradigm in the present world. It is a technology which provides computing resources as a utility like electricity on a metered basis which allows running the workloads similar to grid computing [1]. It delivers its resources such as software, storage, network and databases in reliable, inexpensive and secure means to a large set of users through common internet protocols. These resources are concentrated in large energy greedy data centres. The amount of energy consumption of data centers is doubling-up in every five years. In 2014, U.S. data centers devoured around 70 billion KWh, that in lieu of approximately 2% of aggregate electricity consumption of U.S.A. Based on recent trend, U.S. data centers are estimated to expend around 73 billion KWh in the upcoming year 2020 [2]. Each datacenter is emitting 170 million metric tons of carbon dioxide per year. The anticipated global carbon emissions by data centers in 2020 will be 670 million metric tons per annum. Presently, data centers devour up to 3% of all worldwide power generation while delivering 200 million metric tons of carbon dioxide. Studies shows that the average consumption of data centers can be nearly 25% and energy utilized by the idle resource is can be as regard as 70% of its own peak power. Low Return on the Investment (ROI), system devour up to 3% of all worldwide power generation while delivering 200 million metric tons of carbon dioxide. Studies shows that the average consumption precariousness, as well as much more Carbon dioxide emissions can be created because of this sky-scraping energy burning up of data centers.

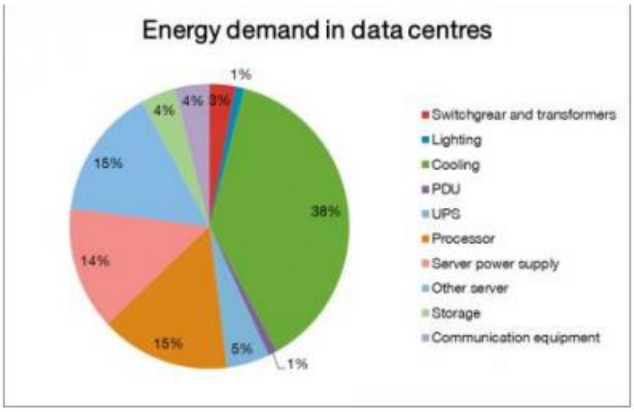

Figure 1: Energy Consumption in Data Centres

2. Related Work

In [3] EES is designed to save the system energy of physical machines in a long term by serving the users over time. EES problem has been formulated systematically and its problem hardness has been analyzed theoretically, then we propose

EESaver (Edge Energy Saver) for formulating EES strategies dynamically over time to facilitate greenMEC. EESaver's superior performance is tested comprehensively.

In [4] presented a modified genetic-based VM consolidation (MGVMC) strategy that aims to replace VMs in an online manner taking into account energy consumption, SLA violations, and the number of VM migrations. The MGVMC strategy utilizes the genetic algorithm to migrate VMs to the appropriate PM in a way that minimizes the number of over-utilized and under-utilized physical machines (PMs) as low as possible. The performance of the MGVMC strategy was evaluated using the CloudSim Plus framework with a large number of VMs and workload traces from the PlanetLab platform. The experimental results revealed that the MGVMC strategy achieved a significant improvement in energy consumption, SLA violations, and the number of VM migrations compared to other recent approaches. These results demonstrate the effectiveness of the MGVMC strategy in optimizing VM consolidation in the cloud environment.

In [5] addresses the problems of decentralization, energy-conservation, and privacy simultaneously. We introduce the first blockchain-based privacy-preserving framework for green IoTs. We name this framework as "Blockchain based Energy-efficient and privacy-preserving data management scheme for GREEN-iot (BENIGREEN)" for smart cities. BENIGREEN uses weight metrics for energy-efficient cluster heads selection. The use of weight metrics is a novel contribution in the field of green IoTs. Further, we integrate a decentralized blockchain framework with an authentication scheme for secure transmission among Base Station (BS) and sensor nodes by employing registration, certification, and revocation phases. Consequently, BS allocates the collected information from cluster heads to decentralized blockchain and cloud storage. The BS eliminates all malicious nodes from the network by employing a certificate revocation process. We execute thorough experiments in terms of the operation time, throughput, average energy consumption, and computational latency. The comparative analysis with the state-of-the-art schemes show that BENIGREEN is efficient for IoT paradigm.

In [6] propose a novel energy efficient multi-objective resource allocation algorithm for heterogeneous cloud radio access networks (H-CRANs) is proposed where the trade-off between increasing throughput and decreasing operation cost is considered. H-CRANs serve groups of users through femto-cell access points (FAPs) and remote radio heads (RRHs) equipped with massive multiple input multiple output (MIMO) connected to the base-band unit (BBU) pool via front-haul links with limited capacity. We formulate an energy-efficient multi-objective optimization (MOO) problem with a novel utility function. Our proposed utility function simultaneously improves two conflicting goals as total system throughput and operation cost. With this MOO, we jointly assign the sub-carrier, transmit power, access point (AP)(RRH/FAP), RRH, fronthaul link, and BBU. To address the conflicting objectives, we convert the MOO problem into a single-object optimization problem using an elastic-constraint scalarization method. With this approach, we flexibly adjust trade-off parameters to choose between two objective functions. To propose an efficient algorithm, we deploy successive convex approximation (SCA) and complementary geometric programming (CGP) approaches. Finally, via simulation results we discuss how to select the values of trade-off parameters, and we study their effects on conflicting objective functions (i.e., throughput and operation cost in MOO problem). Simulation results also show that our proposed approach can offload traffic from C-RANs to FAPs with low transmit power and thereby reduce operation costs by switching off the under-utilized RRHs and BBUs. It can be observed from the simulation results that the proposed approach outperforms the traditional approach in which each user is associated to the AP (RRHs/FAPs) with the largest average value of signal strength. The proposed approach reduces operation costs by 30% and increases throughput index by 25% which in turn leads to greater energy efficiency (EE).

In [7] splitting computing tasks at MEC servers through collaboration among MEC servers and a cloud server, we investigate the joint problem of collaborative task offloading and resource allocation. A collaborative task offloading, computing resource allocation, and subcarrier and power allocation problem in MEC is formulated. The goal is to minimize the total energy consumption of the MEC system while satisfying a delay constraint. The formulated problem is a nonconvex mixed-integer optimization problem. In order to solve the problem, we propose a deep reinforcement learning (DRL)-based bilevel optimization framework. The task offloading decision, computing collaboration decision, and power and subcarriers allocation subproblems are solved at the upper level, whereas the computing resource allocation subproblem is solved at the lower level. We combine dueling-DQN and double-DQN and add adaptive parameter space noise to improve DRL performance in MEC. Simulation results demonstrate that the proposed algorithm achieves near-optimal performance in energy efficiency and task completion rate compared with other DRLbased approaches and other benchmark schemes under various network parameter settings.

In [8] propose a workflow scheduling algorithm named REWS to reduce energy consumption and satisfy workflow reliability constraints. In REWS, a new subreliability constraint prediction strategy is adopted to break down the workflow reliability constraint to task sub-reliability constraints and the effectiveness of this strategy is proved. Moreover, an update method is adopted to adjust the task sub-reliability constraint for reducing energy consumption. In addition, a brief system framework which consists of five parts: workflow analyzer, reliability decomposer, resource manager, workflow scheduler and feedback processer is built to support the algorithm implementation of REWS. We conduct the experiments using both synthetic data and real-world data to evaluate the proposed REWS approach. The results demonstrate the superiority of REWS as compared with the state-of-the-art algorithms.

In [9] considers a joint optimization of computation offloading, service caching, and resource allocation in a collaborative MEC system with multi-users, and formulates the problem as Mixed-Integer Non-Linear Programming (MINLP) which aims at minimizing the long-term energy consumption of the system. To solve the optimization problem, a Deep Deterministic Policy Gradient (DDPG) based algorithm is proposed for determining the strategies of computation offloading, service caching, and resource allocation. Simulation results demonstrate that the proposed DDPG based algorithm can reduce the long-term energy consumption of the system greatly, and can outperform some other benchmark algorithms under different scenarios.

In [10] propose an optimization framework based on deep reinforcement learning, named DeepEE, to jointly optimize energy consumption from the perspectives of task scheduling and cooling control. In DeepEE, a PArameterized action space based Deep Q-Network (PADQN) algorithm is proposed to tackle the hybrid action space problem. Then, a dynamic time factor mechanism for adjusting cooling control interval is introduced into PADQN (PADQN-D) to achieve more accurate and efficient coordination of IT and cooling subsystems. Finally, in order to train and evaluate the proposed algorithms safely and quickly, a simulation platform is built to model the dynamics of IT and cooling subsystems. Extensive real-trace based experiments illustrate that: 1) the proposed PADQN algorithm can save up to 15% and 10% energy consumption compared with the baseline siloed and joint optimization approaches respectively; 2) the proposed PADQN-D algorithm with dynamic cooling control interval can better adapt to the change of IT workload; 3) our proposed algorithms achieve more stable performance gain in terms of power consumption by adopting the parameterized action space.

In [11] considers a computation offloading problem in collaborative edge computing networks, where computation offloading and resource allocation are optimized by means of a collaborative load shedding approach: a terminal can offload a computing task to an edge node, which either can process the task with its computing resource or further offload the task to other edge nodes. Long-term objectives and long-term constraints are considered, and Lyapunov optimization is applied to convert the original nonconvex computation offloading problem into a second problem that approximate the original problem and it is still nonconvex but has a special structure, which gives rise to a new distributed algorithm that optimally solves the second problem. Finally, the performance and provable bound of the distributed algorithm is theoretically analyzed. Numerical results demonstrate that the distributed algorithm can achieve a guaranteed long-term performance, and also demonstrate the improvement in performance achieved over the case of computation offloading without collaborating edge nodes.

In [12] propose a quality-driven and energy-efficient big data aggregation approach for cloud-assisted WBANs. For both the intra-BAN (Phase I) and inter-BAN (Phase II) communications, the aggregation approach is cost effective. Extensive simulation results show that quality-driven energy-efficient big data aggregation for WBANs improves network efficiency in terms of traffic served and energy consumption by 5–7 and 7–8% as compared to the existing schemes.

In [13] addresses these problems by proposing a Dynamic Decision-Based Task Scheduling Technique for Microservice-based Mobile Cloud Computing Applications (MSCMCC). The MSCMCC runs delay-sensitive applications and mobility with less cost than existing approaches. The study focused on Task Scheduling problems on heterogeneous Mobile Cloud servers. We further propose Task Scheduling and Microservices based Computational Offloading (TSMCO) framework to solve the Task Scheduling in steps, such as Resource Matching, Task Sequencing, and Task Scheduling. Furthermore, the experimental results elaborate that the proposed MSCMCC and TSMCO enhance the Mobile Server Utilization. The proposed system effectively minimizes the cost of healthcare applications by 25%, augmented reality by 23%, E-Transport tasks by 21%, and 3-D games tasks by 19%, the average boot-time of microservices applications by 17%, resource utilization by 36%, and tasks arrival time by 16%.

In [14] propose a heuristic that efficiently solves the problem while taking into account the impact of placing services across time periods. We assess the quality of the proposed heuristic by comparing its solution to a lower bound of the problem, obtained by formulating and solving a Lagrangian relaxation of the original problem. Extensive simulations show that our proposed heuristic outperforms baseline approaches in achieving a low energy consumption by packing services on a minimal number of edge nodes, while at the same time keeping the average latency of served requests below a configured threshold in nearly all time periods.

In [15] presented an Adaptive Deep Reinforcement Learning (DRL)-based Virtual Machine Consolidation (ADVMC) framework for energy-efficient cloud data centers. ADVMC has two phases. In the first phase, Influence Coefficient is introduced to measure the impact of a VM on producing host overload, and a dynamic Influence Coefficient-based VM selection algorithm (ICVMS) is proposed to preferentially choose those VMs with the greatest impact for migration in order to remove the excessive workloads of the overloaded host quickly and accurately. In the second phase, a Prediction Aware DRL-based VM placement method (PADRL) is further proposed to automatically find suitable hosts for VMs to be migrated, in which a state prediction network is designed based on LSTM to provide DRL-based model more reasonable environment states so as to accelerate the convergence of DRL. Simulation experiments on the real-world workload provided by Google Cluster Trace have shown that our ADVMC approach can largely cut down system energy consumption and reduce SLA violation of users as compared to many other VM consolidation policies.

3. Energy Management Techniques

Energy conscious scheduling such as DVFS, energy efficient load balancing, virtualization, resource consolidation, and migration are mostly reviewed for knowledge and practical implementations. Many researchers worked for efficient power consumption in Cloud Computing. In this paper author categories, these techniques in different ways and describes the method, improvements, and limitation of these techniques. Fig. 2 shows the types of energy management techniques in cloud computing.

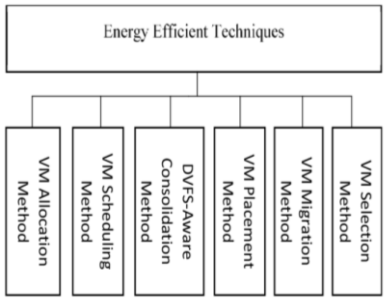

Figure 2 Energy Efficient Techniques in Cloud Computing

A. Virtual Machine (VM) Selection Methods

- Random VM selection: A uniform distributed discrete random variable is used to select the virtual machine from the overloaded server for migration [16].
- Minimum migration time: Migration time of the virtual machine is considered as the ratio of the quantity of RAM utilization of virtual machine to the server’s bandwidth that hosted virtual machine. In this method of VM selection for migration, a VM having minimum migration time is select for migration in comparison to other VMs [17] [18].
- Minimum utilization: Physical resource utilization by the virtual machine is considered as the ratio of the volume of resource utilized by the virtual machine due to user’s tasks allocated to that VM and total MIPS allocated to that VM. And in this method [17] a VM which has minimum utilization has to be select for migration.
- Least VM in CPU utilization first: In this method of VM selection [19], a VM which has share least CPU time with other virtual machines (VMs) allocated to the same server has been selected for migration.
- Maximum correlation: Multiple correlation coefficients are used to calculate the correlation among the virtual machines hosted on the same server. In this method [19] a VM with a maximum correlation of CPU usage with the others VMs has been selected for migration.

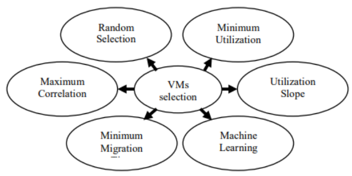

Figure 3 VM Selection Techniques

In random selection, a virtual machine is randomly selected for migration. Minimum migration time is also another factor for choosing the virtual machine which is equal to the amount of memory used by the virtual machine divided by the bandwidth of the host (physical server where the virtual machine is located). In another method, virtual machines that have the lowest processor utilization can be bee chosen for migration. In the maximum correlation technique, the virtual machine is selected based on the highest correlation (in terms of processor efficiency). Utilization slope techniques also employ the utilization history of the virtual machines and compute the slope between the utilization points in each particular time period for each virtual machine and then the virtual machine with a higher total utilization slope is selected for migration.

Machine learning-based virtual machine selection

Due to the fact that choosing the best virtual machine has a remarkable impact on energy management, using intelligent machine learning methods can yield superior performance in this field which can be done by predicting the workload of the virtual machine. Prediction can be defined as the determination of the value of a dependent variable in terms of the values of the independent variable and regression is known as the most important method of numerical prediction[20].

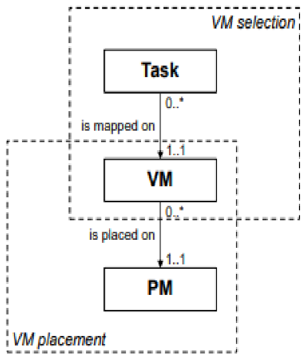

Figure 4 Overview of VM selection and VM Placement

B. Virtual Machine (VM) Placement Methods

For developing Cloud datacentres, energy consumption is the main concern. Several methods and techniques have been proposed to reduce energy consumption, but these techniques are mainly having more VM migration and less resource utilization [21-22].

Virtual Machine placement is the method of choosing the most suitable Physical machine for the VM. If the mapping of virtual machines is fixed throughout, then it is called as static VM placement. If the placement is allowed to change according to the load of the system, then it is called as dynamic VM placement. The dynamic VM placement is further classified into reactive VM placement and proactive VM placement. In reactive VM Placement, only after the system reaches an undesired state, the changes to the initial placement is made. In proactive VM Placement, the changes to initial placement are allowed before the system reaches a certain condition.

Consider we have 5 servers that are not virtualized and hosting 5 applications labeled App1 to App5 as shown in Figure 5. We have application resource requirements for each server. We have to move applications from these servers to virtualized servers on a cloud which is capable of executing multiple VMs in parallel. We can see that from Fig. 6, the hosts that are not virtualized are not fully utilized. The numbers of hosts required can be reduced to 2 by virtualizing the servers as shown in Fig.4 and are utilized to the maximum. Thus consolidating VMs will reduce energy consumption and cost. This mapping of VM to PM is called VM Placement Problem.

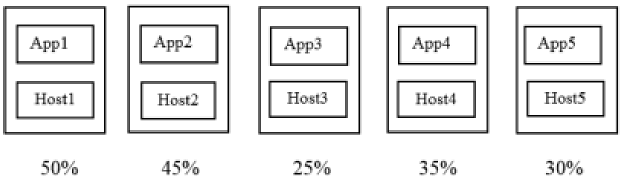

Figure 5 Non-Virtualized servers

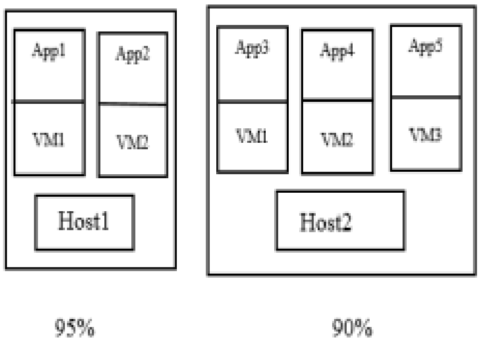

Figure 6 Virtualized servers

An ideal VM Placement technique has the following objectives stated below:

- Improve the scalability of data centers.
- Maximize the utilization of resources.
- Improve load balancing.
- Reduce energy wastage.
- Mitigate energy consumption.
- Deliver the Quality of Service (QOS) guaranteed for the customers.
- Minimize the datacenter traffic.
- Prevent congestion in datacenter network.
- High performance.
- Provide security
- Increase Return on investment (ROI).
- Increase security.
- Reduce the number of active networking elements.
- Minimize SLA violations.
- Decrease VM migrations in the future.

C. Virtual Machine (VM) Migration Methods

An energy consumption model is proposed in [23], which is based on the statistical method and can estimate the VM power consumption with the error rate of 3%-6%. In this method, a workload threshold is set for each server, and if a server exceeds its workload threshold then the VM will be migrated from that overloaded server to another server to reduce the energy consumption by the overloaded server. This method can achieve an effective reduction in power consumption without violating the QoS. A linear integer programming model and bin packaging model are used in [24], to develop two exact algorithms for VMs placement and consolidation for reducing power consumption and VM migration cost and compared with the heuristic based best-fit algorithm. The results show that the combination of these two algorithms contributes to a significant reduction in power consumption.

In [25], the authors have proposed three policies for VM placement and migration. When the number of VM placement increased o server then due to overload the VM migration is required. Which server has to be select for VM migration is dependent on these policies named FDT, DRT, and DDT. These are three different methods for selection of the server for migration according to the threshold set by these policies.

D. DVFS-Aware Consolidation Methods

More than 43 million ton of Co2 emission per year and about 2% of the world's power production has been consumed by the Cloud datacentres. In [24], the author proposed two methods, one for efficient power consumption based on DVFS technique and second for VM consolidation. The first method is used to determine performance degradation with power consumption and gives a DVFS-aware workload management which saves energy up to 39.14% for dynamic workload situations. The second VM consolidation method is also determined dynamic frequency while allocating workload to achieve QoS. There are different types of physical machines are available in Cloud datacentres. This machine heterogeneity consumes more energy when workloads have been scheduled on them. A job consolidation algorithm with DVFS technique is proposed, for efficient resource utilization in heterogenetic Cloud physical machines. The proposed algorithm will replace jobs efficiently to reduce energy consumption.

E. Virtual Machine (VM) Scheduling Methods

The author proposed an online scheduling algorithm for IaaS Cloud model for reduction in energy consumption [26]. The algorithm works for heterogeneous machines and different workload scenario to achieve a better quality of service. One way to reduce energy consumption in Cloud datacentres is to shut down physical servers which are idle. In [27], an energy-aware virtual machine scheduling algorithm has been proposed named as dynamic round robin algorithm. The results showed that the algorithm saves 43.7% energy and 60% of physical machine usage compared with other scheduling algorithms. The authors suggest a model [28] for energy consumption estimation, which considered the running tasks created by virtual machine for estimation of each VM's power consumption. The suggested model also schedules the VMs to confirm the energy cost of each VM. Most of the energy efficient methods use VM migration technique but in [29], the author proposed an energy-aware virtual machine scheduling algorithm EMinTRE-LFT, which is based on the concept i.e., decrease in power consumption is directly equivalent to minimization in the completion time of all physical servers. The author used OpenStack Nova scheduler for simulation and compare it with other algorithms. The Cloud scheduling algorithms face many challenges due to the dynamic and unpredictable nature of Cloud user's request. In [30], the author proposed an algorithm which does not require any prior knowledge of user's request. The author conducted a mathematical analysis to find the balance between energy consumption and system performance. A real-time dynamic scheduling algorithm is proposed in [26], which schedule distributed application in a distributed system to reduce the power consumption. The proposed algorithm uses heuristics and resource allocation techniques to get the optimal solution. It minimizes the power consumption and task execution time with order dependent setup between tasks for VM and power setup for different Cloud designs.

F. Virtual Machine (VM) Allocation Methods

The authors proposed an interior search based virtual machine allocation algorithm for efficient energy consumption and proper resource utilization in [32]. The model and simulation of the proposed algorithm are tested on CloudSim and compared the amount of energy consumption with the Genetic Algorithm (GA) and Best-fit Decreasing (BFD) algorithm. Cloud provider allocates VMs to the customer's application according to their demand, and these VMs are assigned to the physical machines. Many resource allocation methods use VMs resource utilization history for efficient resource allocation. In paper [28], the author proposed a QoS-aware virtual machine allocation method based on resource utilization history to improve the level of quality of services and reduce energy consumption. Cloud datacentres provide services to Cloud applications which consume a huge amount of energy and produce carbon emission. To overcome from this issue, the author proposed an energy-aware VM allocation algorithm in [33], that provision and schedule Cloud datacentre resources to the user's tasks in an efficient manner that reduces energy consumption level of datacentres and improve the quality of service. Many researchers worked for energy efficiency in Cloud Computing, but some researchers are working for energy efficiency in a specific type of Datacentres. In paper [28], the author proposed an efficient power consumption algorithm for video streaming datacentres. They proposed a method for VM management with the power-law feature. It predicts the future resource usage of VM, according to the popularity of video and arranges sufficient resources for that VM and shut down the idle servers on the datacentres to reduce power consumption. The results showed that this algorithm reduced more power consumption compared with Nash and Best-fit algorithm.

4. Conclusion

One of the most important technologies for offering pay-as-you-go services to customers is cloud computing. It provides ITC-based services through the internet and has access to computing resources thanks to the use of virtualization. The key component of cloud computing is the data centre, which houses running programmes and stores corporate data. Everyone in data centres has always had only one priority: high performance. This issue has been handled without taking energy usage and effectiveness into account. Finding a balance between system performance and power usage is difficult. To ensure acceptable energy utilisation in cloud data centres, numerous strategies and algorithms have been proposed. This study reviewed the literature on current methods and strategies for cloud computing energy efficiency.

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