Energy-aware Multi-dimensional Resource Allocation Algorithm in Cloud Data Center

Jiawei Nie, Juan Luo*, and Luxiu Yin
College of computer science and electronic engineering, Hunan University
Changsha, Hunan, 410082, China
[email: juanluo@hnu.edu.cn]
*Corresponding author: Juan Luo

Received November 1, 2016; revised April 23, 2017; accepted May 10, 2017; published August 31, 2017

Abstract

Energy-efficient virtual resource allocation algorithm has become a hot research topic in cloud computing. However, most of the existing allocation schemes cannot ensure each type of resource be fully utilized. To solve the problem, this paper proposes a virtual machine (VM) allocation algorithm on the basis of multi-dimensional resource, considering the diversity of user's requests. First, we analyze the usage of each dimension resource of physical machines (PMs) and build a D-dimensional resource state model. Second, we introduce an energy-resource state metric (PAR) and then propose an energy-aware multi-dimensional resource allocation algorithm called MRBEA to allocate resources according to the resource state and energy consumption of PMs. Third, we validate the effectiveness of the proposed algorithm by real-world datasets. Experimental results show that MRBEA has a better performance in terms of energy consumption, SLA violations and the number of VM migrations.

Keywords: Cloud data center, Dynamic allocation, Multi-dimensional virtual resource, Energy-aware, VM migration

This work is partially supported by Program for The National Natural Science Foundation of China (61672220)

https://doi.org/10.3837/tiis.2017.09.008 **ISSN : 1976-7277**

1. Introduction

Cloud computing is a novel model to provide computing services dynamically, which is supported by data centers, through virtual machine (VM) technology to achieve integration of resources and applications isolation purposes [1]. As a service-oriented business model, cloud providers provide consumers with required computing services by the form of IaaS (Infrastructure-as-a-Service), PaaS (Platform-as-a-Service) and SaaS (Software-as-a-Service) [2]. Under such a business opportunity, Google, Microsoft, IBM and other large enterprises have deployed their own data centers around the world to provide cloud services.

In order to take full advantage of cloud computing, cloud providers need to ensure the ability to flexibly provide services to meet the needs of consumers, while consumers do not care about the underlying infrastructure [3]. Virtualization technology is the key technology to ensure multiple VMs running simultaneously on the same physical node. With such technology, resources in data centers can be allocated with fine-granularity, which not only increases the resource utilization significantly, but also improves the quality of service (QoS) effectively [4].

With the rapid development of cloud computing, the scale of data centers is being enlarged continuously, and energy consumption has become a serious problem [5]. A typical data center energy consumption is equivalent to 25,000 households [6]. Moreover, a recent study [7] showed that the growth of energy consumption in data centers is the fastest in the whole ICT industry. With the increasing cost of energy, more and more researchers are focusing on how to effectively reduce the energy consumption. A generally accepted method in the data center is to consolidate VMs on fewer physical machines (PMs) and make the idle PMs in a sleep mode to save energy [8]. However, this method is too centralized to server overload, which causes the degradation of QoS and violation of SLA (Service Level Agreement). Therefore, an ideal VM allocation policy must find an optimal trade-off between SLA and energy consumption [9, 10].

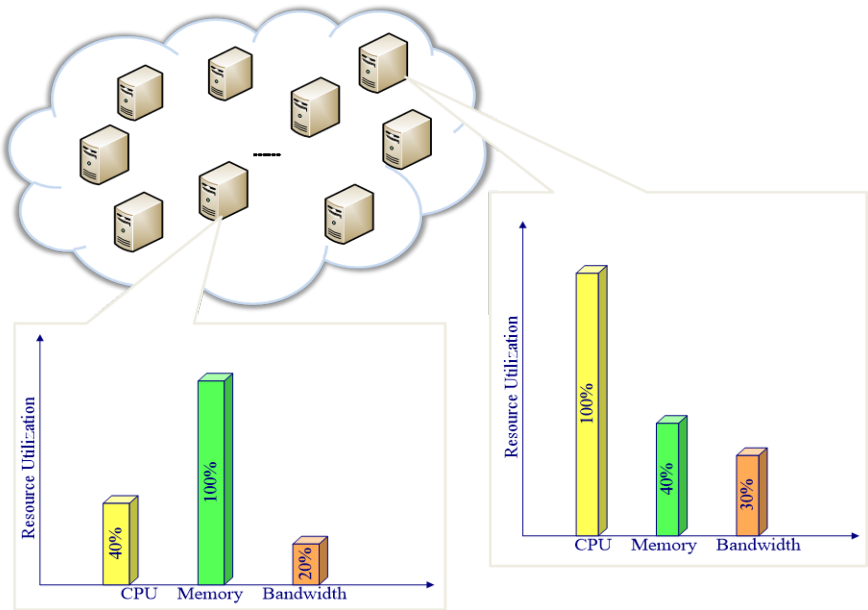

Fig. 1. Resource waste phenomenon in cloud data center

The concept of green cloud computing has aroused great concern in IT industry [11]. Green cloud computing aims at not only improving the efficiency of the infrastructure, but also reducing energy consumption [10]. It is also crucial to ensure the sustainable development of cloud computing. In a cloud data center, user requirements for resource types are various (e.g., CPU, memory size, disk size, bandwidth, etc.). However, most of the existing energy-saving allocation mechanisms have not taken into account the diversity of requests, lacking of research on multi-dimensional resource utilization of physical machines, which causes resource waste phenomenon (as shown in **Fig. 1**) in the data center where one resource is exhausted while other resource are wasted. Accordingly, a resource allocation algorithm for diversified requirements is extremely needed.

Therefore, in order to further promote the development of cloud computing, we need to consider resource usage of each dimension of PMs and manage resources of the cloud data center effectively. Our aim is to maximize resource utilization, and reduce the waste of various resources, as well as decreasing the energy consumption of data centers. There is no doubt that the development of allocation schemes needs to meet QoS requirements specified in the SLA.

In this paper, to solve the waste of resource caused by the heterogeneous workloads, we consider resource utilization among multiple resource dimensions and propose an energy-aware multi-dimensional resource allocation algorithm called MRBEA. Our major contributions are as follows.

1. We build a D-dimensional resource state model and introduce PM distance metrics and VM distance metrics for guiding the deployment of VMs.

2. We propose an efficient VM allocation algorithm MRBEA for maximizing the resource utilization and reducing the energy consumption. Through extensive simulation, we show that MRBEA superiors other algorithms in terms of energy consumption, the number of VM migrations and SLA violations.

The paper is organized as follows. Section 2 discusses the related work, and the system model is introduced in section 3. The detail of allocation algorithm is described in Section 4. Performance analysis of algorithms in Section 5. Section 6 summarizes this article and points out our future research.

2. Related Work

Virtual machine placement (VMP) is similar to the bin packing problem, which is a NP-hard problem [12, 13], whereas dynamic resource management is more complex. This section we introduce some researches related to resource allocation in current cloud data center.

Cardosa et al. [14] have proposed an energy-efficient VMP algorithm in heterogeneous virtualized data center. However, the proposed algorithm is static and they consider only CPU, without supported the stringent SLAs. Considering the multidimensionality of resource, Nguyen Trung Hieu et al. [15] designed a Max-BRU algorithm to achieve the maximum of the resource utilization by reducing the number of active PMs and balance resource utilization of each dimension. The paper did not give a specific performance guarantees, nor the corresponding energy consumption model. To ensure high QoS, Xin Li et al. [4] did research on how to fully increase the resource utilization for improving the performance of the data center and reducing the cost of operating data center. The paper presented a multi-dimensional partition model to guide the VMP. The proposed EAGLE algorithm effectively balance multi-dimensional resource utilization and reduce the energy consumption of data center. However, the dynamics of resource requests is not considered in the paper. LeiWei et al. [16] have pointed out that the existing allocation algorithms focus only on homogeneous resources, which leads to "resource starvation" where dominant resources are starved while non-dominant resources are wasted. To solve the problem, they proposed a SAMR allocation algorithm for heterogeneity to avoid skewed resource utilization in PMs. To ensure performance, they developed a Markov chain model to predict the appropriate number of active PMs. The paper also introduced new notions of VM offering, which has a practical significance.

VM migration is a key technology in the cloud dynamic resource management system. The literature [17] have introduced the VM migration technology and analyzed the importance of it in dynamic resource management in detail. There are three problems in VM migration-based heuristics: (1) When VM to migrate; (2) Which VM to migrate; (3) Which PM for migration. In view of the above questions, Buyya Rajkumar et al. [3] defined a relatively complete green energy-saving cloud computing architecture. They proposed an energy-aware VM allocation algorithm based on dual-threshold, which not only effectively reduces the energy consumption, but also ensures the QoS. Through studying heterogeneity in the workload, Hongyou Li et al. [18] proposed two energy-saving algorithms using workload-aware consolidation technology. The article have pointed out that the resources required for different applications are different. Thus, a computation intensive application can be effectively combined with a memory intensive application or a bandwidth intensive application. A good scheduling algorithm needs to run on the appropriate VMs included in the same PM, to improve the utilization of resources, and thus reduce the energy consumption. Trung Hieu Nguyen et al. [19] proposed a multi-resource selection algorithm (MRS), considering the CPU, memory, storage space, network bandwidth in the cloud data center. The proposed algorithm improves the utilization of the data center and reduces the number of active PMs by consolidating VMs dynamically. However, there is no analysis of the system energy model in detail.

3. System model

In this section, we introduce cloud data center model, D-dimensional resource state model and energy model.

3.1 Cloud data center model

We consider a cloud data center with M PMs and denote a set of M activated PMs as $N=(PM_1, PM_2, ..., PM_M)$. Each PM provides several types of resource such as CPU, memory, bandwidth etc. In the cloud data center, there are lots of PMs with different resource capacity, and all of them are independent of each other. We define a PM as $PM_j=(R^1, R^2, ...R^d)$, where R is capacity of PM, d represents different types of resource and $d \in \{1,2,...D\}$. With virtualization technology, multiple VMs can run on a PM simultaneously. Hence, the corresponding VM is defined as $VM_j=(V^1, V^2, ...V^d)$. These VMs can be migrated between different PMs.

3.2 D-dimensional resource state model

In a data center, each PM contains D-dimensional resources. When any one dimensional resources run out, it means any new VM cannot be placed on the PM. We construct a D-dimensional resource state model to help us to visually grasp the resource usage of PM.

Definition 1 ($PM_j\_RU^d$) Given a PM_j, RU^d is the dth dimensional resource utilization. The $PM_j\_RU^d$ is defined as:

$$PM_j\_RU^d = {PM_j\_C^d_{used}}\Big/{PM_j\_C^d_{total}} \quad , \quad (0 < j \le M, 0 < d \le D) \tag{1}$$

This metric represents the resource utilization of dth dimension of PM_j at current time. $PM_j\_C^d_{used}$ is the dth resource capacity which has been used and $PM_j\_C^d_{total}$ is the dth resource total capacity of PM_j.

In D-dimensional resource state model, each point corresponds to the resource state of a PM, namely: $RU_j(PM_j\_RU^1, PM_j\_RU^2, ..., PM_j\_RU^d)$. As shown in **Fig. 2**, we describe an example in detail when $D=3$. By analogy, we can derive an arbitrary dimensional resource state model. Solid points are current resource state of PMs and axes represent the utilization of various resources. The point S is saturation point, which means that all resources are used up. The point O indicates that the PM is idle.

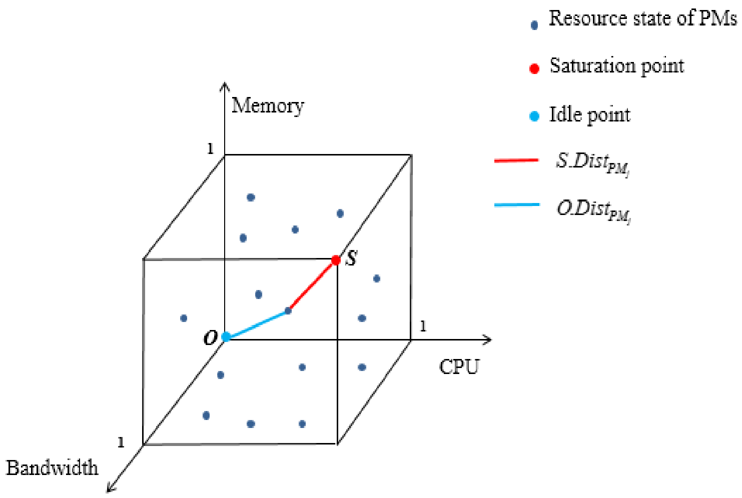

Fig. 2. D-dimensional resource state model (D=3)

Definition 2 ($S.Dist_{PM_j}$) Given a PM_j, the $S.Dist_{PM_j}$ (as shown in **Fig. 2** red line) is defined as:

$$S.Dist_{PM_j} = \sqrt{\sum_{0<d\le D}\left(\frac{PM_j\_C^d_{avail}}{PM_j\_C^d_{total}}\right)^2} \tag{2}$$

The metric $S.Dist_{PM_j}$ represents the distance from RU_j to the point S, where $PM_j\_C^d_{avail}$ is the dth available resource of PM_j.

Definition 3 ($O.Dist_{PM_j}$) Given a PM_j, the $O.Dist_{PM_j}$ (as shown in **Fig. 2** blue line) is defined as:

$$O.Dist_{PM_j} = \sqrt{\sum_{0<d\le D}\left(\frac{PM_j\_C_{used}^d}{PM_j\_C_{total}^d}\right)^2} \tag{3}$$

The metric $O.Dist_{PM_j}$ represents the distance from RU_j to the point *O*.

3.3 Energy model

The power consumption of PMs in the data center depends primarily on the CPU, memory, disk storage and network interface. The study [20] pointed that energy consumption has a nearly linear relationship with CPU utilization. It shows that compared to other system resources, CPU occupies most of the power consumption. Research has shown that the idle server consumes approximately 70% of the power consumed by the server at the full load [21]. Therefore, the idle servers should be set up sleep mode to save energy. In our study, we adopt the energy model as follow:

$$E = P_{fixed} + P_{dynamic} \tag{4}$$

The energy consumption of a PM consists of a fixed part and dynamic part. P_{fixed} is constant power when the server is working. According to [21], P_{fixed} accounts for 70% of total energy consumption. As shown in Eq.(5), the dynamic consumption mainly from the CPU:

$$P_{dynamic} = \left(P_{full} - P_{fixed}\right) * RU_{cpu} \tag{5}$$

where P_{full} is energy consumption of PM at full workload. RU_{cpu} is the utilization of CPU, its calculation is showed in Eq.(1). Because VMs is dynamically changing, so RU_{cpu} is a function of time. The energy consumption of a PM during the time t is shown in Eq.(6):

$$E = P_{fixed} * t + \left(P_{full} - P_{fixed}\right) * \int_0^t RU_{cpu}(t)dt \tag{6}$$

Due to there are a large number of heterogeneous PMs in a data center, so the total energy consumption is shown in Eq.(7):

$$E_{total} = \sum_{i\in N} E_i \tag{7}$$

4. Energy-aware multi-dimensional resource allocation algorithm

With the development of virtualization technology, VMs can be migrated dynamically between different PMs according to performance requirements, which brings a great deal of help to resource management of the data center. This section we present the energy-aware multi-dimensional resource allocation algorithm called MRBEA.

The MRBEA is illustrated by Algorithm 1. We adopt threshold VM selection scheme. First, we set a suitable upper utilization threshold for PMs and keep the utilization of CPU under the threshold. If there exists overloadPM (the the utilization of CPU exceeds the threshold), VM returned by SelectVMtoMigrate() (Algorithm 2 in 4.1) will be migrated from this PM and placed on a suitable PM by FindSuitablePM() (Algorithm 3 in 4.2). Then, we get the "min-PM" with minimum $O.Dist_{PM_j}$ by FindMinloadPM() and try to migrate away all VMs from the PM. If this allocation is successful, the PM is set to sleep mode, otherwise we cancel this allocation and keep the PM active. MRBEA is iteratively repeated until there is no overloadPM.

Algorithm 1: The MRBEA algorithm

```
Input: PMList
Output: allocatedResult
MigrateList←null
PMtoOff_id←null
for PM in PMList do
    if(overloadPM) then
        MigrateList←SelectVMtoMigrate(overloadPM)
        FindSuitablePM(MigrateList , PMList)
    end if
end for
PMtoOff←FindMinloadPM(PMList)
for VM in PMtoOff do
    MigrateList←VM
end for
FindSuitablePM(MigrateList , PMList)
if there exists overloadPM then
    Cancel this Allocation
else
    Sleep(PMtoOff)
end if
return allocatedRuslt
```

4.1 VM selection algorithm

Definition 4 ($Dist_{VM}$) Given a $VM = (V^1, V^2, ...V^d)$, $Dist_{VM}$ is defined as:

$$Dist_{VM} = \sqrt{\sum_{0<d\leq D} \left(\frac{V^d}{PM\_C^d_{total}} \right)^2} \tag{8}$$

The metric represents the distance from VM to the point O.

In order to minimize migration costs and prevent SLA violations, we migrate the VM whose $Dist_{VM}$ is minimum from the PM to reduce utilization. The pseudo-code for VM selection algorithm is presented in Algorithm 2.

4.2 VM placement algorithm

Definition 5 ($Dist_{PM_j}$) Given a PM_j and a VM, $Dist_{PM_j}$ is defined as:

$$Dist_{PM_j} = \sqrt{\sum_{0<d\le D}\left(\frac{PM_j\_C^d_{avail} - V^d}{PM_j\_C^d_{total}}\right)^2} \tag{9}$$

The metric is derived from definition 3, it refers to a new distance between PM_j and the point S when the VM is allocated to the PM_j.

Definition 6 ($Power$) This metric presents the power consumption of PM due to a VM allocation. The specific energy consumption formula is given in Eq.(4-7).

In our study, we introduce the metric PAR (Eq.10) to guide VM placement, which combines the advantages of the above two metrics, considering the d-dimensional resource utilization and energy consumption of the PM.

$$PAR = a * Dist_{PM_j} + b * Power \tag{10}$$

Where a and b are the corresponding weights, and a+b=1.

Algorithm 2: SelectVMtoMigrate(overloadPM)

Input: overloadPM
Output: migratedVM
migratedVM←null
minMetric←null
for VM in PM do
    $Dist_{VM_j} = \sqrt{\sum_{0<d\le D}\left(\frac{V^d}{PM\_C^d_{total}}\right)^2}$
    if $Dist_{VM}$ < minMetric then
        minMetric $\leftarrow Dist_{VM}$
        migratedVM $\leftarrow$ VM
    end if
end for
return migratedVM

Algorithm 3: FindSuitablePM(MigrateList , PMList)

Input: MigrateList , PMList
Output: allocatedPM
ComparisonMetric←Max
allocatedPM←null
for VM in MigrateList do
    for PM in PMList do
        if $PM_j\_C^d_{avail}$ > V^d then
            $Dist_{PM_j} = \sqrt{\sum_{0<d\le D}\left(\frac{PM_j\_C^d_{avail} - V^d}{PM_j\_C^d_{total}}\right)^2}$
            $PAR = \mathrm{a} * Dist_{PM_j} + b * Power$
            if PAR < ComparisonMetric then
                ComparisonMetric ←PAR
                allocatedPM←PM
            end if
        end if

```
        end for
    end for
    return   allocatedPM
```

The pseudo-code for VM selection algorithm is presented in Algorithm 3. To find a best PM, the VM manager traverses the PMList to examine whether there are enough resources for the VM. If a PM has enough resources to host the requested VM, the VM manager calculates the PAR according to Eq.(10). For the PM without enough resources, the VM manager simply skips the calculation and check the next PM. After the checking for all active PMs, the VM manager chooses the PM with the least PAR to host the VM. The least PAR indicates the optimum in improving utilization of various resources and reducing energy consumption.

5. Performance evaluation

5.1 Performance metrics

We use the following metrics to evaluate the performance of our algorithm. The first metric is the total energy consumption of PMs, energy consumption model is introduced in section 3.3. The second is the SLA violation rate (SLA violations) [3], which means the frequency of the SLA violation during the process of system operation. An SLA violation happens when the VM cannot be allocated required MIPS. The third metric is the number of VM migrations.

5.2 Simulation setup

We chose CloudSim3.0 [22] as a simulation platform to implement our proposed algorithm and evaluated its performance. We have simulated a data center that contains 800 heterogeneous PMs, respectively, for the HP ProLiant ML110 G4 servers and HP ProLiant ML110 G5 servers. The configuration parameter of the servers are shown in **Table 1**.

Table 1. Types of PMs

Type	CPU（MIPS）	Memory（GB）	BW（Gbit/s）	Energy(W)
HP ProLiant ML110 G4	1860×2	4	1	86(idle) / 117(full)
HP ProLiant ML110 G5	2660×2	4	1	93.7(idle) / 135(full)

The characteristics of the VM types correspond to Amazon EC2 instance types [23] with the only exception that all the VMs are single-core. The VM types are: high-CPU medium instance (2500 MIPS, 0.85 GB), extra large instance (2000MIPS, 3.75 GB), small instance (1000 MIPS, 1.7 GB), and micro instance (500 MIPS, 613 MB). In our experiments, we chose 6 datasets (as shown in **Table 2**) from [24], which were traced from Planetlab [25].

Table 2. The characteristics of datasets

Dataset	Number of VMs	Mean (%)	St.dev. (%)	Quartile 1 (%)	Median (%)	Quartile 3 (%)
1	1052	12.31	17.09	2	6	15
2	898	12.44	16.83	2	5	13
3	1061	10.70	15.57	2	4	13

4	1054	11.54	15.15	2	6	16
5	1078	10.56	14.14	2	6	14
6	1463	12.39	16.55	2	6	17

5.3 Simulation results

Because experiments involves selection of the threshold, so we first verify the effects of threshold on energy consumption and SLA. As shown in **Fig. 3**, the threshold space for: $\alpha \in (0.6, 1.0)$.

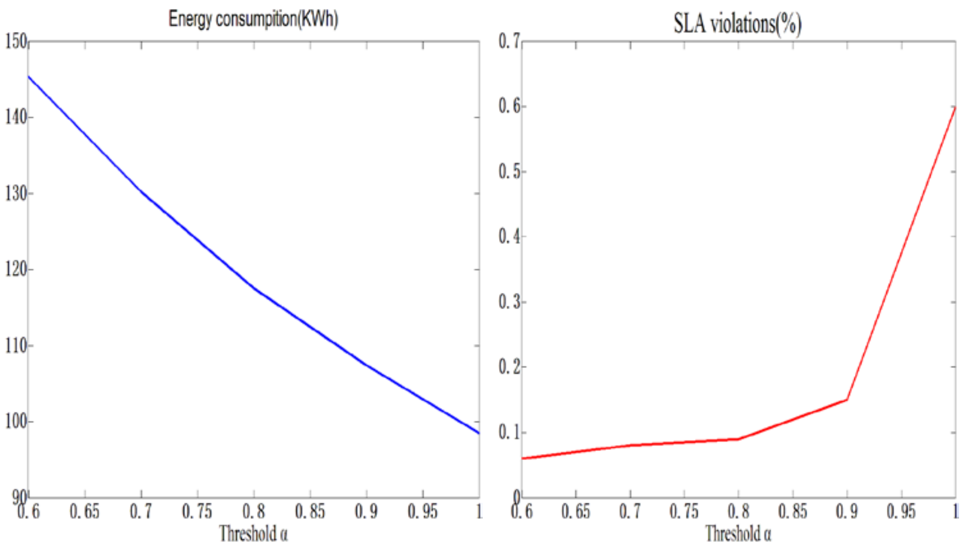

Fig. 3. Relationship between energy consumption or SLA violations and threshold α

The results in **Fig. 3** show that with the growth of the threshold, the energy consumption reduces gradually, while the rate of SLA violations increases. This also confirms that a higher utilization threshold allows more VMs to consolidate on a PM by the cost of sacrificing SLA violations. From **Fig. 3**, we can clearly see that the energy consumption is steadily decreasing, while SLA violations rising sharply from α= 0.9. Hence, to balance energy consumption and SLA, we select α= 0.9.

We compare our algorithm with First-Fit - Minimum Migration Time (FFT-MMT) algorithm and Power Aware BFD (PABFD)-MMT algorithm which is introduced by Beloglazov et al. [24] in next experiments. These two algorithms focus on virtual resource allocation. FFT-MMT utilizes MMT policy to choose a VM to migrate and adopts the idea of FFT to find a destination PM. By this method, MMT migrates a VM that requires the minimum time to complete a migration [24], that is to say, it selects the VM with minimum memory to migrate. Then a VM is allocated to a PM by FFT which is scanned firstly and meet resource requirement. PABFD-MMT algorithm adopts MMT during the VM migration process. Considering energy consumption of PMs, the VM would be allocated to the PM that consumes the least energy caused by the allocation.

Fig. 4 shows the total energy consumption of PMs in data center. We can see the energy consumption of FFT is maximum, this is because FFT just simply judge whether there are enough resources for VMs in PMs, without considering energy efficiency. Compared to the other two algorithms, the proposed algorithm has less energy consumption. This also indicate that during the allocation of resources, considering only energy consumption of a single PM cannot make the minimum energy consumption of the entire data center. We needs combine the multi-dimensional resource usage and energy consumption to choose the most suitable VM allocation mechanism.

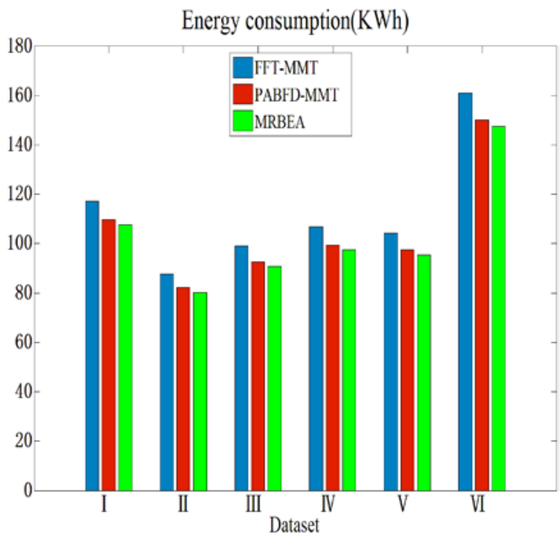

Fig. 4. The energy consumption

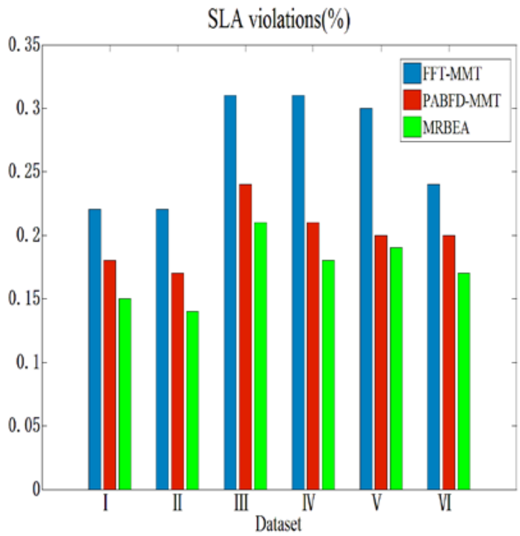

Fig. 5. The SLA violations

Fig. 4 shows the total energy consumption of PMs in data center. We can see the energy consumption of FFT is maximum, this is because FFT just simply judge whether there are enough resources for VMs in PMs, without considering energy efficiency. Compared to the other two algorithms, the proposed algorithm has less energy consumption. This also indicate that during the allocation of resources, considering only energy consumption of a single PM cannot make the minimum energy consumption of the entire data center. We needs combine the multi-dimensional resource usage and energy consumption to choose the most suitable VM allocation mechanism.

In **Fig. 5**, we can clearly see that the adoption of the MRBEA algorithm results in a significantly decreased SLA violations in comparison to other algorithms. The MRBEA has reduced the energy consumption, while balancing the resource utilization across all PMs and improving SLA violations. The less SLA violations for the cloud providers can reap greater benefits, but also provides users with a higher level of performance guarantees.

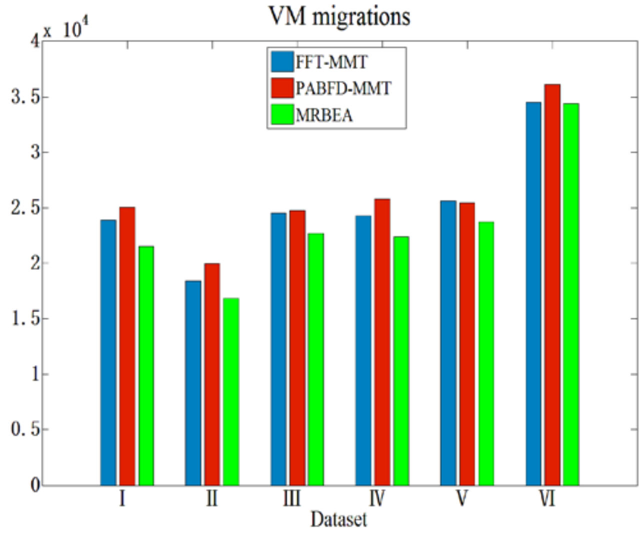

Fig. 6. The number of VM migrations

The results in **Fig. 6** show that our proposed MRBEA algorithm completes the cloud task with less number of migrations. As we known, frequent VM migrations may led to performance degradation, and the more migrations, there will be an increase in violation of SLA. The MRBEA algorithm improves the efficiency of resource allocation by considering each dimension of resource utilization and heterogeneous workload, thereby reducing the unnecessary migrations.

6. Conclusion

In the article, we addressed the phenomenon of resources waste in data center for improving the resource utilization among multiple dimensions. Based on D-dimensional resources state and energy consumption model, we propose an energy-aware multi-dimensional resource allocation algorithm called MRBEA. The proposed algorithm efficiently reduces energy consumption and achieves a better performance. The simulation results have shown that the MRBEA superiors other algorithms in terms of energy consumption, the number of VM migrations and SLA violations. As a future work, we seek to implement and evaluate our algorithm in a real-world experiment (e.g. Openstack).

References

[1] P. Barham, B. Dragovic, K. Fraser, S. Hand, T. Harris and et al, "Xen and the art of virtualization," *ACM SIGOPS operating systems review*, vol. 37, no. 5, pp. 164-177, December, 2003. Article (CrossRef Link).

[2] Q. Zhang, L. Cheng and R. Boutaba, "Cloud computing: state-of-the-art and research challenges," *Journal of Internet Services and Applications*, vol. 1, no. 1, pp. 7-18, May, 2010. Article (CrossRef Link).

[3] A. Beloglazov, J. Abawajy and R. Buyya, "Energy-aware resource allocation heuristics for efficient management of data centers for Cloud computing," *Future Generation Computer Systems*, vol. 28, no. 5, pp. 755-768, May, 2012. Article (CrossRef Link).

[4] X. Li, Z. Qian, S. Lu and J. Wu, "Energy efficient virtual machine placement algorithm with balanced and improved resource utilization in a data center," *Mathematical and Computer Modelling*, vol. 58, no. 5, pp. 1222-1235, September, 2013. Article (CrossRef Link).

[5] N. D. Han, Y. Chung and M. Jo, "Green data centers for cloud-assisted mobile ad hoc networks in 5G," *IEEE Network*, vol. 29, no. 2, pp. 70-76, April, 2015. Article (CrossRef Link).

[6] M. Poess and R. O. Nambiar, "Energy cost, the key challenge of today's data centers: a power consumption analysis of TPC-C results," in *Proc. of the Vldb Endowment*, vol. 1, no. 2, pp. 1229-1240, August, 2008. Article (CrossRef Link).

[7] M. P. Mills, "The cloud begins with coal: Big data, big networks, big infrastructure, and big power," *Digital Power Group*, 2013.

[8] Z. Á. Mann, "Allocation of Virtual Machines in Cloud Data Centers—A Survey of Problem Models and Optimization Algorithms," *Acm Computing Surveys(CSUR)*, vol. 48, no. 1, pp. 1-34, September, 2015. Article (CrossRef Link).

[9] S. Srikantaiah, A. Kansal and F. Zhao, "Energy aware consolidation for cloud computing," in *Proc. o f Conference on Power aware computing and systems*, pp.1-5, December, 2008. Article (CrossRef Link).

[10] R. Buyya, A. Beloglazov and J. Abawajy, "Energy-Efficient Management of Data Center Resources for Cloud Computing: A Vision, Architectural Elements, and Open Challenges," *Eprint Arxiv*, vol. 12, no. 4, pp. 6-17, July, 2010. Article (CrossRef Link).

[11] J. Luo, S. Fu and D. Wu, "Energy-aware Virtual Resource Mapping Algorithm in Wireless Data Center," *Ksii Transactions on Internet & Information Systems*, vol. 8, no. 3, pp. 819-837, March, 2014. Article (CrossRef Link).

[12] X. Li, Z. Qian, R. Chi, B. Zhang and S. Lu, "Balancing Resource Utilization for Continuous Virtual Machine Requests in Clouds," in *Proc. of Sixth International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing(IMIS)*, pp. 266-273, July 4-6, 2012. Article (CrossRef Link).

[13] K. Xie, X. Wang, J. Wen and J. Cao, "Cooperative routing with relay assignment in multiradio multihop wireless networks," *IEEE/ACM Transactions on Networking (TON)*, vol. 24, no. 2, pp. 859-872, April, 2016. Article (CrossRef Link).

[14] M. Cardosa, M. R. Korupolu and A. Singh, "Shares and utilities based power consolidation in virtualized server environments," in *Proc. of Ifip/ieee International Symposium on Integrated Network Management*, pp. 327-334, June 1-5, 2009. Article (CrossRef Link).

[15] N. T. Hieu, M. Di Francesco and A. Y. Jääski, "A virtual machine placement algorithm for balanced resource utilization in cloud data centers," in *Proc. of IEEE International Conference on Cloud Computing(CLOUD)*, pp. 474-481, June 27-July 2, 2014. Article (CrossRef Link).

[16] L. Wei, C. H. Foh, B. He and J. Cai, "Towards Efficient Resource Allocation for Heterogeneous Workloads in IaaS Clouds," *IEEE Transactions on Cloud Computing*, pp. 1-1, September, 2015. Article (CrossRef Link).

[17] M. Mishra, A. Das, P. Kulkarni and A. Sahoo, "Dynamic resource management using virtual machine migrations," *IEEE Communications Magazine*, vol. 50, no. 9, pp. 34-40, September, 2012. Article (CrossRef Link).

[18] L. Hongyou, W. Jiangyong, P. Jian, W. Junfeng and L. Tang, "Energy-Aware Scheduling Scheme Using Workload-Aware Consolidation Technique in Cloud Data Centres," *China Communications*, vol. 10, no. 12, pp. 114-124, December, 2013. Article (CrossRef Link).

[19] T. H. Nguyen, M. D. Francesco, and A. Yla-Jaaski, "A Multi-resource Selection Scheme for Virtual Machine Consolidation in Cloud Data Centers," in *Proc. of IEEE 6th International Conference on Cloud Computing Technology and Science(CloudCom)*, pp. 234-239, December 15-18, 2014. Article (CrossRef Link).

[20] X. Fan, W. D. Weber and L. A. Barroso, "Power provisioning for a warehouse-sized computer," *ACM SIGARCH Computer Architecture News*, vol. 35, no. 2, pp. 13-23, May, 2007. Article (CrossRef Link).

[21] L. Hu, H. Jin, X. Liao, X. Xiong and H. Liu, "Magnet: A novel scheduling policy for power reduction in cluster with virtual machines," in *Proc. of IEEE International Conference on Cluster Computing*, pp. 13-22, September 29-October 1, 2008. Article (CrossRef Link).
[22] R. N. Calheiros, R. Ranjan, A. Beloglazov, C. A. De Rose and R. Buyya, "CloudSim: a toolkit for modeling and simulation of cloud computing environments and evaluation of resource provisioning algorithms," *Software Practice and Experience*, vol. 41, no. 1, pp. 23–50, January, 2011. Article (CrossRef Link).
[23] Amazon EC2. Article (CrossRef Link).
[24] A. Beloglazov and R. Buyya, "Optimal online deterministic algorithms and adaptive heuristics for energy and performance efficient dynamic consolidation of virtual machines in Cloud data centers," *Concurrency and Computation: Practice and Experience*, vol. 24, no. 13, pp. 1397–1420, September, 2012. Article (CrossRef Link).
[25] K. Park and V. S. Pai, "CoMon: a mostly-scalable monitoring system for PlanetLab," *ACM SIGOPS Operating Systems Review*, vol. 40, no. 1, pp. 65-74, January, 2006. Article (CrossRef Link).

Jiawei Nie received the bachelor's degree in communication engineering in 2014 from Hunan Institute of Engineering, Hunan, China. He is currently studying for a master's degree in college of information science and engineering, Hunan University, Hunan, China. His research is focused on cloud computing and virtual resource allocation.

Juan Luo received the bachelor's degree in electronic engineering in 1997 from National University of Defence Technology, Hunan, China. She achieved master's and PhD degrees in communication and information system in 2000 and 2005, respectively, both from Wuhan University, Hubei, China. She is currently a professor in college of computer science and electronic engineering, Hunan University, Hunan. From 2008 to 2009, she was a visiting scholar in Irvine, California University, US. Her research is focused on wireless network, cloud computing and wireless sensor network.

Luxiu Yin received the bachelor's degree in Computer Science and Technology in 2011 from Changsha University, Hunan, China. He achieved master's degree in Computer software and theory in 2015 from Hunan Normal University, Hunan, China. He is currently studying for a PhD degree in college of information science and engineering, Hunan University, Hunan, China. His research is focused on cloud computing and wireless virtual network.