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Cooling aware job migration for reducing cost in cloud environment

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Abstract With the growth in computing needs, energy cost includes a large portion of operating cost of cloud data centers. Electricity prices vary in different times and geographical places. Such diversity provides opportunity for diminishing total cost via migration of jobs to places with lower energy prices. Most of the previous studies only focus on computing cost of data centers and disregard other significant parameters such as cooling cost of data centers. These approaches prefer data centers which are located in states with cheaper computing cost. Nonetheless, inappropriate workload migration may lead to a remarkable increase in the total cost because of ignoring the cooling cost of data centers. To address this challenge, we show that minimization of the total cost must cover both the computing and cooling cost while considering delay requirements of jobs. Moreover, we propose an analytical approach which captures the interaction between migration decisions and cooling cost in cloud data centers. Features that make our approach distinct from other similar approaches are the following: first, we consider that cooling cost increases in a nonlinear way with respect to the data center utilization; second, we model cooling cost without any assumption about how the data center cooling system works. In order to achieve energy saving,

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we determine how much workload should be migrated to other data centers and also the number of servers allocated to each data center for executing the workload. We accomplish migration of workload between data centers by utilizing variety in electricity prices in different locations and times and achieve lower total cost compared with previous schemes. Eventually, using MapReduce traces, we validate our method and indicate that remarkable cost saving, around 37 % can be obtained by cooling-aware job migration.

Keywords Cloud computing · Cooling aware migration · Cost efficiency

1 Introduction

Energy efficiency has become a vital issue in cloud environments as the popularity of such infrastructures rises and also prices of energy resources increase. Based on the information reported in 2011, about 1.5 % of all worldwide electricity has been consumed by data centers and servers. Furthermore, the energy consumption has witnessed 56 % growth compared with previous studies conducted in 2006 [1,2].

Several studies have been proposed to reduce energy cost using different approaches in this context. Concentration of some of these studies is on reducing energy consumption within data centers such as Dynamic Voltage and Frequency Scaling (DVFS), consolidation and engineering advances in cooling [3–6]. However, these methods ignore the impact of variability of energy prices in different times and locations.

In another line of study, temporal and geographical features of electricity price for reducing energy cost have gained research attention. In cloud environments, data centers are placed in different geographical locations. For instance, Google has several data centers in various regions of the US to utilize variation in energy prices and gain more reliability [7]. Since the energy expense may differ significantly across two different regions, migration of workloads to the data centers with lower energy cost substantially can reduce the total energy cost in those environments.

In the course of recent years, using diversity in energy prices to reduce total energy cost has been considered in several approaches [7–17]. These methods consider different factors to achieve their main goal i.e., cost reduction. One of the basic approaches in this line of research only considers energy price in allocating workloads to the data centers [7,11]. Another group of studies consider the bandwidth cost and distance among data centers in addition of energy price [12,17]. Main focus of these kinds of studies is restricted to computing cost. However, none of those studies includes the cooling cost in the calculation of the total energy cost.

A modern data center typically expends extra half a Watt for cooling power per one Watt of power consumed by the computing infrastructure [18]. Although data centers recently are equipped with better cooling systems, cooling energy consumption still includes a substantial portion of the total cost of data centers [19]. All of these methods emphasize the importance of cooling cost in migration decision to reduce the total cost. The goal of this paper is to take into account the cooling cost to make the cloud computing more efficient in terms of energy expenditure.

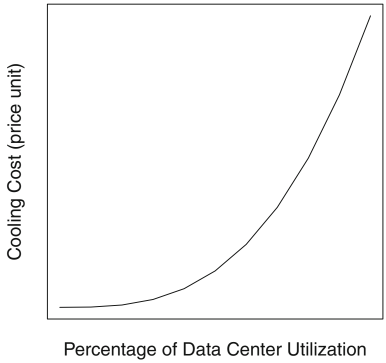

Fig. 1 Approximate trend in cooling cost as a data center's utilization increases [18]

Recent studies have investigated the impact of the expenses imposed by cooling systems on the total cost in the process of workload assignment to each data center. Studies such as [17] and [20] estimate cooling cost as the product of PUE (Power Usage Effectiveness) and computing power. In their studies, the aforementioned cost is calculated as a linear function of the data center utilization. In this work, we first show there is a nonlinear relationship between the cooling cost and utilization of data centers which is the main distinction of our work with other similar studies. Afterward, based on this observation, we propose a new model for calculation of cooling cost and finally incorporate it in our migration problem.

Figure 1 is an informal sketch which shows the relationship between the cooling cost and data center utilization and reveals the motivation of our approach [18]. The cooling cost of a data center is plotted as a function of the data center utilization. In higher utilization, this figure indicates that cooling cost rises more rapidly than data center utilization. Given that each data center has different quality in physical structure, knee of cooling cost curve for each data center is not similar to others. A well laid-out data center has a curve with a knee at high utilization, and various studies have been proposed to obtain such cooling cost curve such as [18] and [19].

In this paper, we propose a migration scheme between data centers which considers the impact of cooling cost in migration decision. Our approach takes into account migration cost, computing cost and cooling cost and addresses two main issues. First, we determine how much workload should be migrated and to which data centers. Second, we calculate the number of servers which should be run in each data center. Moreover, these decisions are taken with this limitation that delay (which includes both network delay and queuing delay) must not exceed from a delay threshold. We evaluate our method using numerous experiments by MapReduce traces and show that our approach effectively reduces the total energy cost by approximately 37 %.

The rest of this paper is organized as follows: Section 2 discusses the related state of the art research. Section 3 presents the system model including the cost model and constraint model. Section 4 introduces the modeling and formulation of the migration problem. Section 5 provides the proposed approach. Section 6 shows the experimental results. Finally, Sect. 7 concludes the paper.

2 Related work

The topic of energy efficiency in cloud environments has attracted many research interests. We discuss those related work, which can be categorized as follows:

Energy efficiency in data centers: one group of studies has focused on the energy efficiency through applying consolidation and DVFS and dynamic capacity provisioning [3–5]. Turning on or off servers in a cloud data center based on the dynamics of workload is considered in [15]. Beloglazov et al. [21] survey different studies that have been conducted in the context of data center energy management. While these studies concentrate on reducing the energy usage in one data center, we focus on reducing cost via exploiting geographical diversity of energy prices.

Cost efficiency in data centers: some scholars recently make use of the spatio-temporal variation in electricity prices to reduce the total cost in data centers. Qureshi et al. [11] aim to reduce the electricity bill by benefiting from the variety in electricity price in different data centers. The authors apply heuristics to quantify the potential economic gain regarding diversity in electricity price. By using real workload, they show that rational distribution of computation by considering the issue of various electricity pricing in different locations can lead to save millions of dollars in the total cost of data centers. However, they did not benefit from migration of workload to diminish the total cost and also did not consider the impact of cooling cost in the total cost of data center.

Rao et al. [7] represent a load balancing technique over data centers for minimizing energy cost by considering delay constraints. The authors benefit from linear programming techniques and min-cost flow model to find a near-optimal solution. They did not consider cooling cost in their total cost formulation and also considered the average energy cost of active servers in their calculations. However, we enhance the power consumption model of active servers to be dependent on their current utilization.

Abbasi et al. [17] propose a method which determines the number of active servers in each data center that are required to execute the assigned workload and also the amount of workload that should be given to each data center. Total cost is considered as the summation of computing cost and cooling cost and they propose an optimization solution to minimize this total cost. However, they assumed that cooling cost is obtained by multiplying computing cost by PUE. Unlike their work, in this paper, we propose a new cooling cost model which includes nonlinear relationship between cooling cost and computing cost and we incorporate it in our migration problem.

Liu et al. [13] propose a geographical load balancing method for reducing the electricity price related to so called brown energy (i.e., coal and oil) with the usage of renewable energy sources. Nonetheless, they do not consider the cooling cost in geographical load balancing formulation. In contrast, our approach considers cooling cost in accomplishing migration of workload between data centers.

Finally, to decrease the electricity bill, Buchbinder et al. [12] illustrate an online method for job migration between different data centers. However, this method neglects the impact of cooling cost in migration problem. Consequently, we indicate that the impact of the expenses imposed by cooling systems in total cost cannot be ignored and should be considered in the migration problem.

Table 1 Symbols and definitions

Symbol	Definition
t	Time slot index
i, j	Index of data centers
L_i	Initial workload at ith DC
Y_i	Executed workload at ith DC
$\delta_{i,j}$	Migrated workload from ith DC to jth DC
M_i	Total number of servers at ith DC
m_i	Number of active servers at ith DC
p_i^{idle}	Server idle power at ith DC
p_i^{util}	Server peak power minus idle power at ith DC
μ_i	Service rate of servers at ith DC
U_i	Utilization of ith DC
α_i, β_i	Cooling cost parameters of ith DC
$b_{i,j}$	Migration constant value between ith DC and jth DC
e_i	Electricity price at ith DC
d'	Queuing delay
d''	Network delay between data centers
D	Total delay of a request
d_r	Reference delay

3 System model

In this section, we describe the system model and the migration model which are used in our proposed method. First of all, we determine the components of the problem and then we propose an optimization formulation for workload migration. This formulation includes many attributes from recent methods for defining workload characteristics and performing job migration and consequently expands the applicability of our approach. Table 1 summarizes the notations which are used throughout the paper.

3.1 Workload model

We suppose that workload varies over time and the time model itself is discrete. The size of each time slot is selected in a way to be appropriate for updating migration decision. We assume $t \in \{1, \ldots, T\}$ as the time interval, while T can be a large value. T may be equal to a month and a time slot can be determined by 1 h. It is supposed that requests (jobs) initially are allocated to the data centers for processing. Afterward, these requests may be migrated to other data centers to be processed with lower cost. Initial allocation to ith data center at time slot t is denoted by $L_{i,t}$ which shows the job arrival rate to ith data center. In Sect. 6, we apply real-world traces for $L_{i,t}$ in order to have more accurate estimations.

3.2 Data center model

Consider N data centers are placed in different geographical places. The number of servers in ith data center is equal to M_i. Servers are homogeneous and have the service rate equal to μ_i. Workload can be migrated between different data centers and $\delta_{i,j,t}$ indicates the amount of workload migrated from ith data center to jth data center at time slot t. Therefore, the amount of workload that must be executed in ith data center at time t is modeled as follows:

$$Y_{i,t} = L_{i,t} + \sum_{j=1}^{N} \delta_{j,i,t} - \sum_{j=1}^{N} \delta_{i,j,t} \tag{1}$$

It is equal to sum of the allocated workload and migrated-in workload minus the migrated-out workload. Total workload must be balanced before and after migration at time slot t. As a result, the following condition must be satisfied:

$$\sum_{i=1}^{N} L_{i,t} = \sum_{i=1}^{N} Y_{i,t} \tag{2}$$

It is obvious that the total cost can be reduced by two principal decisions via migration: first, how much workload should be migrated from ith data center to jth data center (i.e. $\delta_{i,j,t}$); second, how many active servers are required to execute workload at time slot t in each data center (i.e. $m_{i,t}$). We model the total cost by incorporating computing cost, cooling cost and migration cost while delay requirements are considered. It should be noted, to reduce the complexity of the model, switching cost related to servers which cycle in and out of power-saving modes is not included in our total cost model. Nevertheless, if considering such costs would be needed, a model for incorporating them has been proposed in [15].

3.3 Computing cost model

Computing cost of a data center is a function of power consumption of its servers and the electricity price. We assume that power consumption of a data center is a summation of its idle power consumption and active power consumption. Note that p_i^{idle} is the average idle power consumption for each server at ith data center; the cumulative idle power consumption of data center is equal to $m_i p_i^{\text{idle}}$, where m_i is the number of active servers and is calculated as $\lceil \frac{Y_{i,t}}{\mu_i} \rceil$. Let p_i^{util} be the active power consumption of each server at full utilization minus the idle power. If active power consumption of ith data center at full utilization equals $M_i p_i^{\text{util}}$, the total power consumption of ith data center is calculated as

$$U_{i,t}(M_i p_i^{\text{util}}) + m_{i,t} p_i^{\text{idle}},$$

where $U_{i,t}$ is the utilization of ith data center at time slot t and is calculated by $U_{i,t} = \frac{Y_{i,t}}{M_i \mu_i}$. After some simplification, the computing cost of ith data center at time slot t is

$$C_i^{\text{computation}}\left(Y_{i,t}, m_{i,t}\right) = \sum_{i \in N} \left(\frac{Y_{i,t}}{\mu_i} p_i^{\text{util}} + m_{i,t} p_i^{\text{idle}} \right) e_{i,t}, \tag{3}$$

where $e_{i,t}$ is the electricity price in ith data center at time slot t. Note that $\delta_{i,j,t}$ is a variable which is determined by the minimization. Also, $Y_{i,t}$ is determined according to $\delta_{i,j,t}$ and by using Eq. 1.

3.4 Cooling cost model

The total cost of data centers is remarkably affected by the cooling power as well as the computing power. First of all, we delineate that there is an association between cooling power and computing power. Afterwards, by considering this dependency, we describe a formulation for modeling the cooling power.

Motivation Data centers have to employ cooling facilities to moderate emitted heat from the computing devices. As the utilization of a data center increases, the amount of produced heat rises. Data centers must prevent temperature from exceeding a manufacture-specified threshold, i.e. red-line temperature [19]. For keeping temperature below this threshold, cooling system is forced to consume more energy to supply enough cold air. Increase in cooling cost leads to increase in total cost of data centers.

Figure 1 indicates that cooling cost increases in a non-linear way with respect to the data center utilization. Cooling cost approximately increases exponentially with respect to the data center utilization. The knee of the curve is different for each data center and depends on the physical layout of data center [18]. It must be noted that increase in utilization of data center leads to drastic increase in cooling cost.

Model It is assumed that each cooling curve approximately can be best fitted to a curve similar to Fig. 1. As a result, cooling cost can be represented by the following formulation. In order to calculate cooling cost, we have scaled down utilization of data center to the range between 0 and 100 and used it in the following formulation:

$$C_i^{\text{cooling}}\left(U_{i,t}\right) = \left(\alpha_i e^{\beta_i U_{i,t}}\right) e_{i,t}, \tag{4}$$

where α_i and β_i are cooling parameters which are different for each data center. These parameters are technology-dependent and show the quality of physical layout of data center which is out of the scope of this paper. It is also assumed that kw is the unit of cooling power. By having these two parameters of cooling cost, we calculate cooling cost and incorporate it in migration decision that leads to substantial cost saving.

3.5 Migration cost model

In migration process of workload between data centers, the bandwidth cost is an indispensable cost that must be considered in the total cost. The amount of migrated workload has a direct effect on the cost of migration which is modeled as following:

$$C_{i,j}^{\text{migration}}\left(\delta_{i,j,t}\right) = b_{i,j} \delta_{i,j,t}, \tag{5}$$

where $b_{i,j}$ denotes a constant value for workload migration from data center i to j irrespective of the migration time [12]. It should be noted that arrival of jobs into the cloud and leaving the cloud is associated with bandwidth costs. Nonetheless, we are able to incorporate these costs without changing the problem formulation because they are independent of migration control and are considered constant.

3.6 Total cost model

To calculate the total energy cost of ith data center at time slot t with respect to above models, it is sufficient to sum its computing cost with its cooling cost and migration cost.

$$C^{\text{total}} = \sum_{t=1}^{T}\sum_{i=1}^{N}\Big(C_i^{\text{computation}}\left(Y_{i,t}, m_{i,t}\right) + C_i^{\text{cooling}}\left(U_{i,t}\right)\Big) + \sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{j=1}^{N} C_{i,j}^{\text{migration}}\left(\delta_{i,j,t}\right) \tag{6}$$

3.7 Constraint model

Any single job is not permitted to be allocated to any data center. There are some constraints that limit the execution of some jobs at some certain places. The delay constraints can be considered as the significant factor. For example, long distance between two data centers might impede the migration of jobs between them because of creating inevitable delay. We define a reference delay d_r for jobs to keep quality of service (QoS) in an acceptable level. This reference delay is considered as a threshold which should not be violated.

Delay is comprised of two elements: network delay and queuing delay. The amount of time that a job experiences outside of a data center is equal to network delay d'' and the amount of time that a job spends in the queue until it can be executed is equal to queuing delay d'. As a result, total delay is equal to $D = d'' + d'$.

The queuing delay at ith data center at time slot t is defined by $d'_{i,t}$. We consider $M/M/n$ queue to model each server in data center. This model has been used in the literature [7,22–24]. In the $M/M/n$ queueing model, the average delay can be calculated as follows:

$$d'_{i,t} = \frac{1}{m_{i,t}\mu_i - Y_{i,t}}, \tag{7}$$

where $m_{i,t}$ is the number of active servers with service rate μ_i. The entire workload which should be executed in ith data center at time t is denoted by $Y_{i,t}$. In order to keep stability, we should be assured that $Y_i = 0$ or $Y_i < m_i\mu_i$. In a situation where $Y_i \geq m_i\mu_i$, we would have $d_i = \infty$ [9].

Moreover, it is supposed that network delay is equal to $d''_{i,j}$ and indicates the amount of delay experienced by a job being transferred from ith data center to jth data center.

This delay depends on the network distance from ith data center to jth data center. We model $d''_{i,j}$ as the distance between data center i and data center j (divided by the speed of 200 km/ms plus a constant 5 ms) similar to that of [13]. Therefore, total delay can be calculated as follows:

$$D_{i,j,t} = d''_{i,j} + d'_{i,t} \tag{8}$$

Similar to [25], it is assumed that d_r is equal to 66 ms.

4 Problem formulation

According to the above models, the migration problem is formalized in our approach. We aim to minimize the total cost at time interval $[1, T]$ by selecting the migrating jobs $\delta_{i,j,t}$ and the number of active servers at ith data center $m_{i,t}$, while the constraints are satisfied. Therefore, the following optimization problem is proposed:

$$\min_{\delta_t, m_t} \sum_{t=1}^{T} \sum_{i=1}^{N} \left(C_i^{\text{computation}} \left(Y_{i,t}, m_{i,t} \right) + C_i^{\text{cooling}} \left(U_{i,t} \right) \right) + \sum_{t=1}^{T} \sum_{i=1}^{N} \sum_{j=1}^{N} C_{i,j}^{\text{migration}} \left(\delta_{i,j,t} \right) \tag{9a}$$

$$\text{subject to} \quad \sum_{i=1}^{N} L_{i,t} = \sum_{i=1}^{N} Y_{i,t} \qquad \forall i \in N \tag{9b}$$

$$\sum_{j=1}^{N} \delta_{i,j,t} \leq L_{i,t} \qquad \forall i \in N \tag{9c}$$

$$Y_{i,t} < m_{i,t} \mu_i \qquad \forall i \in N \tag{9d}$$

$$\delta_{i,j,t} \geq 0 \qquad \forall i \in N, \ \forall j \in N \tag{9e}$$

$$0 \leq m_{i,t} \leq M_i \qquad \forall i \in N \tag{9f}$$

$$m_{i,t} \in \mathbb{N} \qquad \forall i \in N \tag{9g}$$

$$d_r - D_{i,j,t} \geq 0 \qquad \forall i \in N, \ \forall j \in N \tag{9h}$$

The total workload should be balanced before and after migration [constraint (9b)]. Moreover, the total workload that has been migrated out from ith data center at time slot t cannot exceed the amount of initial workload which was allocated to ith data center at time slot t [constraint (9c)]. In addition, the total workload at ith data center, cannot be more than the computing capacity of data center [constraint (9d)].

Without loss of generality, we can divide the optimization problem into a series of sub-problems which are independent at each time slot t. As a result, we consider a single interval for each analysis. By regarding these restrictions, the migration problem is modeled as follows:

$$\min_{\delta,m} \quad \sum_{i=1}^{N} \left(\frac{Y_i}{\mu_i} p_i^{\mathrm{util}} + m_i p_i^{\mathrm{idle}} + \alpha_i e^{\beta_i \frac{Y_i}{M_i \mu_i}} \right) e_i + \sum_{i=1}^{N} \sum_{j=1}^{N} b_{i,j} \delta_{i,j} \tag{10a}$$

$$\text{subject to} \quad \sum_{i=1}^{N} L_i = \sum_{i=1}^{N} Y_i \qquad \forall i \in N \tag{10b}$$

$$\sum_{j=1}^{N} \delta_{i,j} \le L_i \qquad \forall i \in N \tag{10c}$$

$$Y_i < m_i \mu_i \qquad \forall i \in N \tag{10d}$$

$$\delta_{i,j} \ge 0 \qquad \forall i \in N, \ \forall j \in N \tag{10e}$$

$$0 \le m_i \le M_i \qquad \forall i \in N \tag{10f}$$

$$m_i \in \mathbb{N} \qquad \forall i \in N \tag{10g}$$

$$d_r - D_{i,j} \ge 0 \qquad \forall i \in N, \ \forall j \in N \tag{10h}$$

One solution to this problem would be to determine how many servers in each data center should be allocated to the workload (i.e. m_i) and how much workload should be migrated between data centers (i.e. $\delta_{i,j}$).

5 Proposed algorithm

Considering the aforementioned models in Sect. 4, our migration approach is described in Algorithm 1. Let $V_t = \{m_{i,t}, \delta_{i,j,t}\}$ denote the optimization variable. As shown in Algorithm 1, the inputs at the beginning of each time slot t include current energy prices, cost parameters and initial workload of each data center. The algorithm determines how much workload should be migrated between data centers (i.e. $\delta_{j,i}$) and how many servers in each data center should be allocated to the workload (i.e. m_i) in the current time slot to minimize the total energy cost.

We use *the Karush–Kuhn–Tucker conditions* [26] to determine the optimal point V_t^* for the optimization variables ($\delta_{j,i}$ and m_i). We implemented our proposed migration approach based on *fmincon* which is a standard nonlinear programming solver provided by the optimization toolbox of MATLAB.

It is notable that the aforementioned migration problem is jointly convex in $\delta_{i,j}$ and m_i and can be solved centrally. Thus, we assume that a central controller is responsible for performing the optimization using the collected information from data centers. As a result, the optimal number of servers and amount of workload that

Algorithm 1: The Algorithm of Migration

1: $t \leftarrow 1$;
2: **repeat**
3: At the beginning of time slot t;
4: **Inputs:**
5: / Initial allocation to each data center at time slot t: $L_{i,t}$;/
6: / Current energy prices at each data center at time slot t: $e_{i,t}$;/
7: / Cost function parameters for each data center: $\{p_i^{\text{idle}}, p_i^{\text{util}}, M_i, \mu_i, \alpha_i, \beta_i, b_{i,j}\}$;/
8: Solve the problem by *fmincon* function in MATLAB;
9: **output**: The optimal point $V_t^* = \{m_{i,t}, \delta_{i,j,t}\}$
10: **until** $t = T$

should be migrated between data centers are derived and passed to each data center. Moreover, the optimization frequency should be fast enough to capture the electricity price variation, and also slow enough to prevent overhead of network and computation. It is worth mentioning that we chose the decision interval to 1 h. Although our scheme can be applied even if the electricity prices vary at lower frequencies, e.g., every 15 min, server's wear-and-tear and other issues may prevent adjustments at this rapid time-scale. Thus, we set length of each time slot to 1 h so servers will not be turned on/off too fast considering the non-negligible wear-and-tear cost.

6 Experimental results

In this section, we evaluate our proposed method under realistic conditions.

6.1 Experimental setup

As mentioned before, our objective in this paper is minimizing the total cost of data centers using diversity in time and location prices. Our method benefits from realistic parameters in the experimental setup. Thus, we can provide conservative estimates for the cost savings resulting from migration of workload among different data centers.

Data center description In order to provide acceptable service level, cloud provider needs abundant computational resources. For instance, Google includes numerous data centers located around the world. At least, there are 12 remarkable Google IDC installations in different places of the United States. In this paper, we model our cloud environment by considering ten of these locations: California, Washington, Oregon, Illinois, Georgia, Virginia, Texas, Florida, North Carolina, and South Carolina (red points in Fig. 2) [27].

Electricity price According to the raw electricity price data collected from US government agencies [28,29], we calculate the average electricity price per hour at each data center and the electricity prices are shifted according to each data center's time zone. The time zone of each state are listed in Table 2.

Workload description Two popular available traces are used in our simulation, i.e. MapReduce traces. These popular traces are gathered in one day and have strong dynamical properties over time [30]. We consider time slot with length of 1 h. The

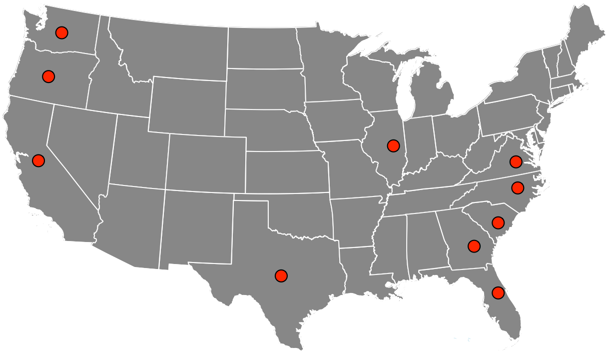

Fig. 2 Data centers locations

Table 2 Time zone of each state

State	Time zone
California	GMT_8
Washington	GMT_8
Oregon	GMT_7
Illinois	GMT_6
Georgia	GMT_5
Virginia	GMT_5
Texas	GMT_6
Florida	GMT_5
North Carolina	GMT_5
South Carolina	GMT_5

number of jobs in each time slot is counted and applied as dynamic workload for simulation (Fig. 3). We shift traces to the time-zone of the data centers locations. We also scale traces for ith data center in a way that the peak workload (max $L_{i,t}$) be equal to maximum capacity of data center ($M_i \mu_i$).

Cost function parameters The Formula (10) is applied to model the total cost of the system. This formulation has two cooling parameters α and β which should be set to acceptable values. We extract $\alpha = 8$ and $\beta = 0.04$ from the results of DIGITALMINHR algorithm in [18]. We take advantage of the data center model which is used in [18] to have realistic assessment. There are 1,120 servers within each data center. The type of servers is HP Proliant DL360 G3s and their measured power consumption in two levels, idle and 100 % utilization, is equal to 150 and 285 W, respectively. Thus we can consider $p^{\text{idle}} = 150$ W and $p^{\text{util}} = 135$ W for each server. As mentioned in Sect. 3.3, the amount of active power consumption of each server at full utilization minus the idle power is considered as p^{util}.

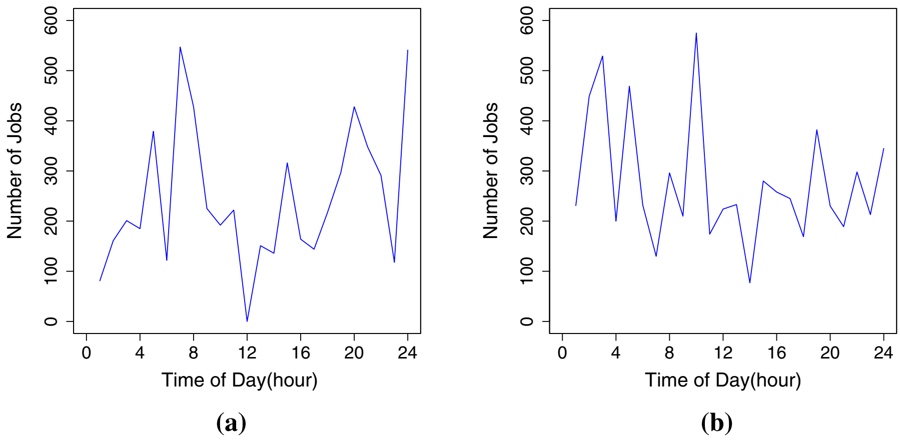

Fig. 3 Illustration of dynamic workloads. **a** Workload A, **b** workload B

It is assumed that all servers at each location are similar to each other and we set $\mu_i = 1$ for all i. we assume $b_{i,j}$ is equal to the bandwidth cost of transferring a job out of data center i [12]. We assume that bandwidth price for job migration between different data centers varies between \$0.20 to \$0.60 per GB, and the task memory footprint is 4 GB according to the average intermediate results in phases of two MapReduce traces. We consider $b_{i,i}$ as a large number in order that it is not possible to migrate the workload from source to source.

Cost benchmarks We provide two benchmarks to evaluate our proposed method, i.e. approximation of commonly used methods in Internet-scale systems. Moreover, these benchmarks are used to compare with previous proposals implicitly such as [7,12]. We also compare out proposed method with benchmark 3 which does not utilize any algorithm. The approaches use various amount of data to minimize the cost. Note that queueing delay should be considered by each approach.

The first benchmark considers both computing cost and migration cost simultaneously and neglects cooling cost while minimizes its cost. This benchmark can highlight the strength of cooling aware migration in total cost reduction. Thus, it provides opportunity for comparing our method with those approaches such as [12] implicitly.

The second benchmark only considers computing cost and ignores both of migration cost and cooling cost.

6.2 Simulation results

In this section, evaluation and analysis of our approach in terms of cost saving is presented. We benefit from MATLAB to perform our simulations in this paper. In order to solve the convex problem, we used *fmincon* as a convex solver package in MATLAB. This solver is widely used in the literature [31–34].

Cost savings We compare cost saving of our approach with three baseline strategies that are described in the experimental setup. Figure 4 shows that our approach outper-

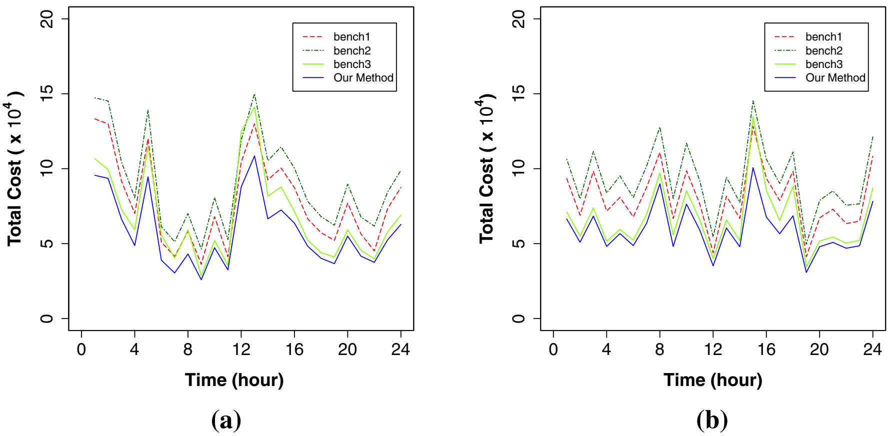

Fig. 4 Total cost of different approaches under both workloads. **a** Workload A, **b** workload B

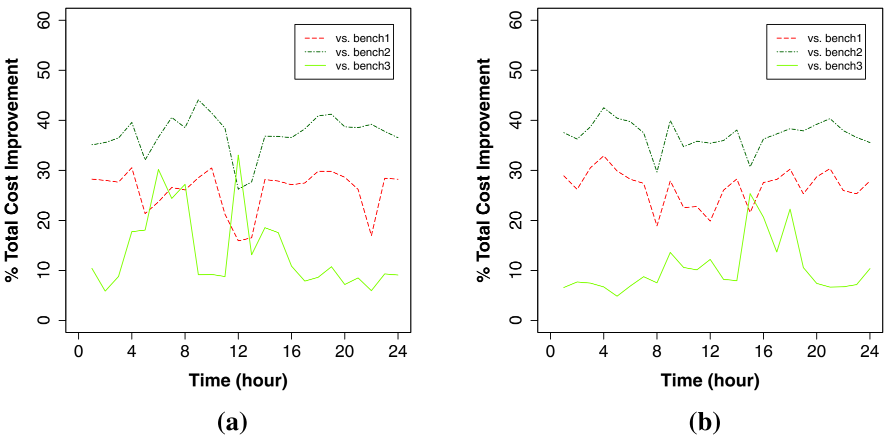

Fig. 5 Total cost (% improvement of our method vs. other benchmarks). **a** Workload A, **b** workload B

forms other baselines in terms of cost saving under both workloads. Figure 5 shows improvement of our method compared to three baselines. As the figure indicates, our result has improvement over baseline 1, baseline 2 and baseline 3 by 25.9, 37.2 and 13.7 % for workload A and by 26.7, 37.1 and 10.4 % for workload B, respectively.

In order to have better comparison, we consider individually two major components of cost including the cooling cost and computing cost. Figure 6 reveals that our approach outperforms other baselines in cooling cost which is mainly due to the fact that those baselines ignore cooling cost in their decisions. It is obvious that our approach cannot perform as well as baseline 1 and 2 in terms of computing cost, as it can be seen in Fig. 7. The explanation for this observation is that baseline 2 merely concentrates on computing cost and baseline 1 only focuses on computing cost and migration cost. However, our approach considers cooling cost in addition to these costs to minimize the total cost. Nevertheless, our method has negligible difference in

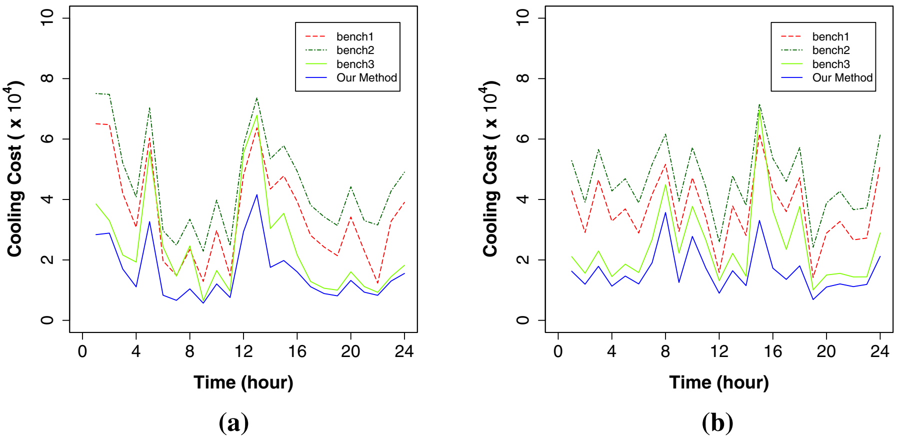

Fig. 6 Cooling cost of different approaches under both workloads. **a** Workload A, **b** workload B

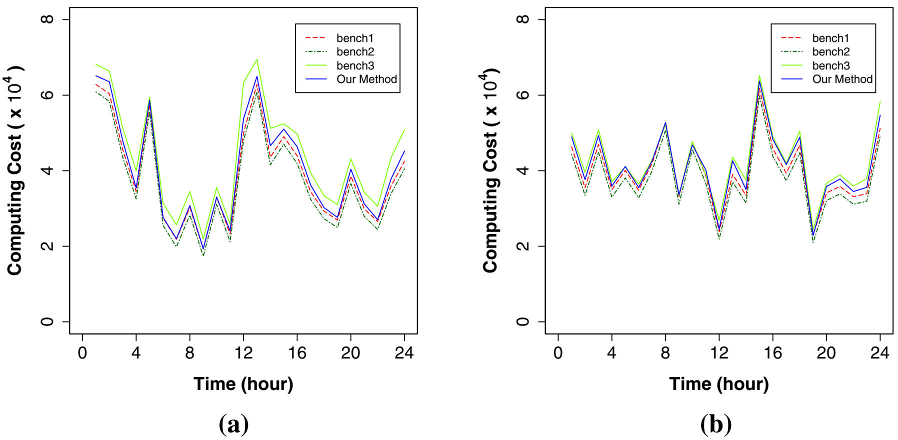

Fig. 7 Computing cost of different approaches under both workloads. **a** Workload A, **b** workload B

computing cost comparing to those two baselines. As Fig. 4 indicates that although baselines 3 does not apply any algorithm, it mostly outperforms two other baselines. The explanation for this is that, since main focus of the two other baselines is on the computing cost, they neglect the impact of cooling cost in their migration decision which leads to inaccurate workload migration. Therefore, migration without considering all effective costs leads to poor result than approach which does not apply any algorithm.

Furthermore, when traffic rate is too low or too high, efficiency of our method is similar to that of other approaches. In a light traffic period in which utilization of data centers is low, cooling cost cannot affect the total cost in migration problem. Also, in a high traffic period, data centers approximately are saturated with workload and there is no choice to migrate workload. As the Fig. 4 indicates, advantage of cooling aware migration becomes more evident whenever traffic rate in data centers is average

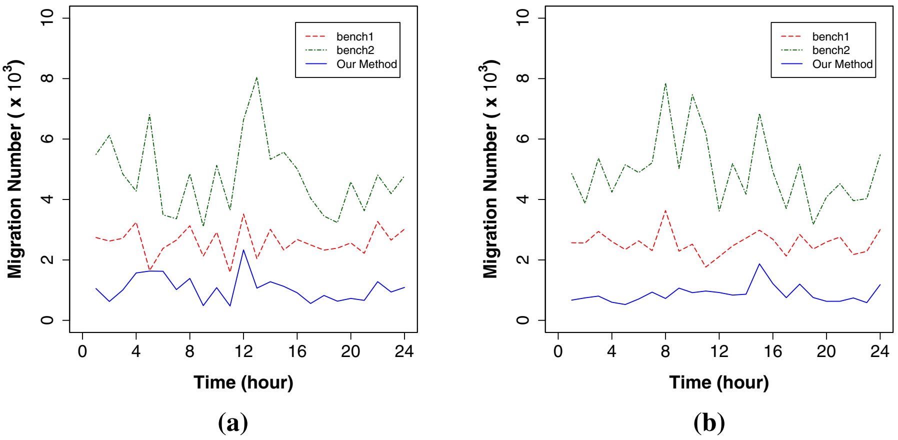

Fig. 8 Migration number of different approaches. **a** Workload A, **b** workload B

and data centers operate at mid-level utilization. Then, we are able to decide how and where workload can be migrated. Data centers usually operate at mid-level utilization where our approach has the best performance [18].

Another insightful parameter is the number of migration which our method and tow other baselines (baseline 1 and 2) may perform. As Fig. 8 shows, our method mostly has fewer migration number compared with two other baselines; however, this does not mean that our approach always performs less number of migration to minimize the total cost.

Cooling cost parameters analysis As mentioned in Sect. 3, data centers have different cooling cost parameters which represent their distinct quality in physical layout. It should be noted that these parameters have a decisive role in cost management. We evaluate the impact of these parameters on our proposed model.

In order to have better evaluation, we consider both parameters of α and β individually. First, we consider β as a fixed number ($\beta = 0.04$) and change α in the interval 7 to 9. Then, we keep α fixed ($\alpha = 8$) while changing β between 0.03 to 0.05. Figure 9 indicates how the total cost is changed by increasing α under workload A. Also, Fig. 10 shows how the total cost changes as β increases under workload B. Figures 9 and 10 imply that increase in α and β leads to more difference between our total cost and that of other baselines. Cost improvement of our approach is enhanced by increasing these two parameters, specially increase in β parameter. Moreover, increase in α and β leads the difference between benchmark 1 and 2 become less. The explanation for this occurrence is that the cooling cost gains more weight in the total cost by increasing these cooling parameters and this is where our approach outperforms other baselines.

6.3 Discussion

It is assumed a job first arrives at a central controller (dispatcher) in which load balancing decisions are made. The main focus of our paper is related to the migration

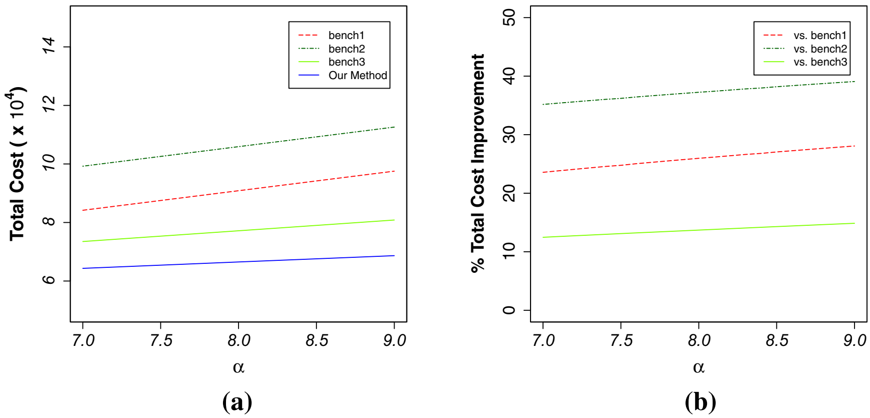

Fig. 9 Impact of α on total cost ($\alpha = 7{-}9$, $\beta = 0.04$). **a** Total cost, **b** total cost (% improvement of our method vs. other benchmarks)

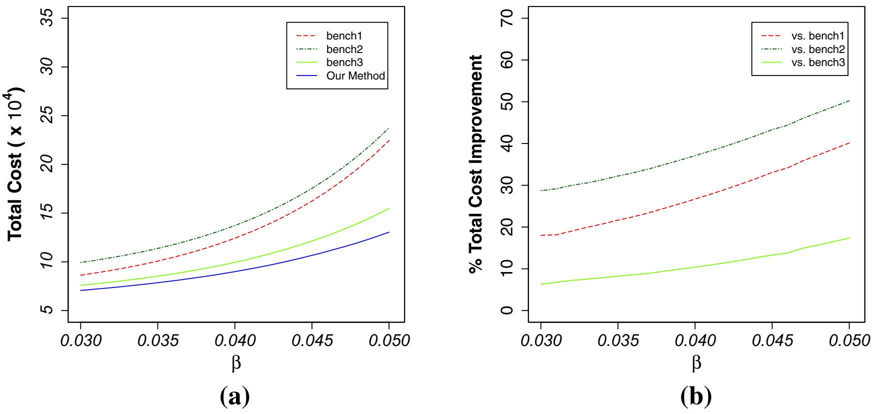

Fig. 10 Impact of β on total cost ($\alpha = 8$, $\beta = 0.03{-}0.05$). **a** Total cost, **b** total cost (% improvement of our method vs. other benchmarks)

level and not to the dispatching level; however, our approach also can be used in the job assignment decision. In this way, the central controller can make load balancing decision by considering the total workload arrived at each time t. Assignment of workload to the data centers can be done by considering different cost of data centers. As we mentioned before, the energy prices vary unpredictably in different time and location and to capture the electricity prices and reduce the total energy consumption, workload which is assigned to one data center can be migrated to another data center and this is where our approach is applicable. Note that there is no need to migration if we have already known all information about energy prices. However, we assume that the electricity prices vary unpredictably based on the different time and location.

As may be expected, it is not worth to migrate a short running job because its gain is negligible considering the migration costs. Therefore, we only consider long running tasks in our proposed method. Hence, we take advantage of MapReduce workloads in our simulation. These workloads contain deadline in the range of minutes (8–30 min) and they have been used in the literature [35–37].

As a matter of fact, various workload classes might have different SLA and delay requirements. To express the problem, the cost model requires other parameters and simply incorporating a class of workload into the model may not change the problem nature. Also, this flexibility is given to our approach to move workload of lower class to the most cost-efficient data centers which results more cost savings. A comprehensive study of this modeling is left for future work.

In our proposed approach, we model each server in data center using $M/M/n$ queuing model. Although this model is simple, it has been widely used in the literature [7,22–24]. However, considering other queue model is a very good direction for our future studies.

Furthermore, we assume in our simulation that inputs about workload and electricity price are available in the start of each slot. However, these parameters must be predicted in practical situations. Although the workload and electricity price can be predicted, the estimation error may reduce the overall cost saving marginally. The proposed migration scheme can be seen as a central controller which must be updated frequently with information about electricity price and the history of workload from data centers. As this information must be applied at each time slot which is normally about an hour to several hours, the overhead is insignificant.

7 Conclusion

Operating cost of cloud environment is on the rise with the increase in energy prices and also energy consumption of data centers. We benefit from spatio-temporal variation of energy price in different places to diminish the total energy cost of data centers. Our approach deals with this problem in a comprehensive view which takes into account cooling cost in addition to computing and migration costs. Furthermore, in our migration problem, it is assumed that cooling cost increases in a nonlinear way with respect to data center utilization. In this paper, we indicate that a data center with lower energy price cannot always be the best choice for migration, since increase in load of data center could lead to remarkable increase in the cooling cost and subsequently converting a cheap data center to expensive one. Moreover, by performing extensive simulations under realistic workload traces and electricity prices, we show that cooling aware migration of workload between data centers has significant reduction impact on the total cost. Nevertheless, performance of our method depends on the certain factors like the variation in price and the cooling cost parameters of different data centers. There are a number of fascinating directions for future work that can be suggested by the findings from this study. For instance, switching cost (i.e. turning on or off servers) is one factor which can be considered in migration decision. Some aspects such as reliability and security constraints also can be considered in the future work. In addition, some properties of tasks like task dependency and atomic task could be considered as our future work. Moreover, Other factors such as different climate conditions and availability of renewable energy in data centers could be taken into account during migration decisions. We would like to take into account these factors for migration decision in the future.

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