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A green-aware virtual machine migration strategy for sustainable datacenter powered by renewable energy

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ABSTRACT

With the rapid growth of cloud services, huge energy consumption of the underlying large-scale datacenters becomes a major concern of both the resource providers and the society. Datacenter owners are beginning to use renewable energy as extra supply for the devices. In this paper, we design a green-aware power management strategy for such datacenters powered by sustainable energy sources, considering the power consumption of both IT functional devices and cooling devices. Specifically, we make use of energy-aware methods to formulate an overall optimization problem, and try to solve it by combining heuristic and statistical searching approaches. The ultimate objective is to utilize green energy sufficiently while keeping the demand of applications deployed inside the datacenter at an acceptable level. Performance evaluation and simulation experiments are designed upon a simulated testbed, with realistic workload traces and solar energy generation considered, in order to validate the feasibility of our approach. Results show that it can significantly improve the green energy utilization, and achieve the highest overall revenues for the resource provider.

1. Introduction

As the key infrastructure of cloud service environments, large-scale datacenters become high performance platforms integrating massive data computing and storage, providing online computing services for millions of customers simultaneously. Such datacenters for Internet-based services are usually comprised of hundreds of heterogeneous server nodes, that consume significant amount of energy. This leads to a high carbon footprint of these datacenters since fossil fuels are used to produce such energy mostly. It is estimated that world-wide datacenters consume approximately 1.5% of all electricity worldwide in 2011 [1]. Furthermore, the energy consumption of datacenter grows quickly, at a speed of approximately 10–12% per year [2]. Hence, considering the heavy emissions and increasing impact on climate change, governments, organizations and also IT enterprises are trying to find cleaner ways to manage the datacenters.

Since the generation of renewable energy is usually intermittent and unstable, it brings many challenges for us to reliably and efficiently provide renewable energy. As the workloads of large-scale datacenters are also variable, we believe that a

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coordinated resource management and power management approach could help datacenters to use renewable energy more effectively.

On the other hand, in order to attract and retain customers, it is important and crucial to provide QoS (Quality of Service) guarantees for hosted applications. Hence, how to allocate resources efficiently to the deployed applications while respecting Service Level Agreements (SLA) [3] is a challenging issue for resource providers. Usually, users will specify QoS requirements via SLAs, including users' demand on service quality levels by different kinds of metrics, and also the cost and penalty involved in the service process. Considering that end-users could tolerate a little performance degradation when accessing the services, it is possible to study how to balance the SLA-based profit maximization while minimizing the consumption of traditional brown energy.

Since services are usually deployed in virtual machines (VM), resource management in cloud environments could be easier by migrating VMs across different physical nodes of the datacenter [4,5]. In this paper, we propose a green-power-aware virtual machine migration strategy to manage resources and power in green datacenters powered by mixed supply of both grid and renewable energy. First, we introduce some existing approaches for utilizing renewable energy in single green datacenters. Then, we also put insights into thermal-aware and renewable-energy-aware methods in sustainable datacenters. In the following sections, we outline our research framework and describe the relevant models and strategies in detail. Performance evaluation experiment results illustrate that our approach can catch the renewable energy variation quite well, by compromising the SLA profits of deployed applications and diminishing unnecessary energy waste as much as possible. Moreover, the advantage of our approach over the other two traditional approaches are depicted in further experimental results. Finally, conclusion remarks and some discussion of possible future work will be given in the last section. We hope that this paper could pave the way for researchers to utilize the unique characteristics of datacenter workloads and reduce their dependence on traditional brown energy.

2. Related work

2.1. Energy-aware scheduling and resource management

Over the past decade, issues of green computing and energy efficiency gain more and more attention, and thus many studies start to conduct research on managing workload fluctuation and try to achieve a better trade-off between system performance and energy consumption. Karatza, Terzopoulos, Stavrinides, and Zikos developed a series of energy management through Dynamic Voltage Scaling (DVS) and scheduling and have applied these techniques in real-time heterogeneous clusters [6–9]. Sharma et al. [10] have implemented several adaptive algorithms for dynamic voltage scaling in QoS-enabled web servers inside the Linux kernel, which could minimize energy consumption by using a feedback loop that regulates frequency and voltage levels. Tanelli et al. [11] adopted DVS of CPUs as control variables and tried to address the performance control issues in Web servers, aiming at reducing energy consumption. Berl et al. [12] did a survey some of the current best practice and relevant progress in the area of energy efficient technology, and tried to identify some remaining key challenges in cloud computing environments. Urgaonkar et al. [13] made use of queuing information available in the system to make online decision and aimed at jointly optimizing the application throughput and energy costs.

These studies attempt to save energy as much as possible while trading off the performance. Comparatively, our research jointly considered renewable energy into the optimization, which would lead to different scenarios when green energy is sufficient enough to support performance enhancement.

2.2. Thermal-aware power management

Since the energy management usually involves temperature considerations, thermal-aware resource management in datacenters attracted much interest of researchers recently. For example, Mukherjee et al. [14] investigated some techniques to incorporate temperature-awareness into high-level objectives, and developed two temperature-aware algorithms in order to minimize the maximum temperature, thus preventing hot spots. Tang et al. [15] proposed a task scheduling algorithm called *XInt* that can minimize the inlet temperatures and achieve minimal cooling energy cost for datacenter operation. Pakbaznia et al. [16] combined chassis consolidation and efficient cooling to achieve datacenter-wide power saving and at the same time not exceeding the upper bound of the required maximum temperature of any server chassis in the datacenter. Wang et al. [17] proposed two thermal-aware task scheduling algorithms and presented them in the paper based on analytic models, which can lower the temperatures and the cooling system energy consumption in a datacenter. In our work, we also consider the impact of temperature on cooling power consumption, which comes from two kinds of cooling devices. Furthermore, we incorporate the impact of the outside temperature as well, which helps to examine the effect of air free cooling.

2.3. Renewable energy utilization for datacenters

Some researchers have been studying on how to efficient utilize renewable energy inside a single datacenter. For example, Deng et al. [19] proposed the concept of carbon-aware cloud applications, in which carbon-heavy energy is treated as a

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primary cost, and designed some policies and mechanisms for provisioning resources on demand inside a datacenter powered by renewable energy. Giori et al. designed a framework called GreenSlot [21] which aims to schedule batch workloads, and another framework called GreenHadoop [22] which orients MapReduce-based tasks. Krioukov et al. [23] presented an energy agile cluster that is power proportional and exposes slack, and invented a grid-aware scheduler using workload slack to reduce dependence on non-renewable energy sources to 40% of its original level. Li et al. [24] proposed a light-weight server power management method called *iSwitch*, which switches between wind power and utility grid following renewable power variation characteristics. Arlitt et al. [20] from HP Labs introduced and designed a "Net-Zero energy" datacenter, which uses on-site renewable generators to offset the usage of brown energy from the grid. Tsai et al. studied cloud storage management by dynamically configuring the types of storages to reduce the cost and energy consumption [25]. Liu et al. [26] presented a holistic approach that integrates renewable energy supply, dynamic pricing, cooling supply and workload planning to improve the overall attainability of the datacenter.

These work has made a lot of effort on sufficiently utilizing green energy in datacenters. Similarly, our work also focused on such concepts. Specifically, we exploit the possibility of efficient VM migration management following the variation of the renewable energy supply. The framework in this paper has incorporated the flexibility of transactional workloads, cooling power consumption and also the amount of available green energy. We are trying to solve the problem by jointly optimizing the power consumption of both IT devices and cooling devices, considering the impact of temperature as well.

3. System architecture overview

This section describes the architecture of the green datacenter powered by hybrid energy and the virtualized datacenter environment discussed throughout this paper.

3.1. Green datacenter powered by hybrid energy

The architecture of a typical green datacenter with hybrid energy supplies is as shown in Fig. 1. The upper part of the figure shows the supplying part of the whole system, which integrates the traditional grid utility and renewable energy. The ATS (Automatic Transfer Switch) is in charge of combining different energy supplies together and provide the energy to the datacenter. The dashed round-corner rectangle shows the consumption part of the green datacenter. Functional equipment inside the datacenter consumes energy for dealing with fluctuating incoming workloads. At the same time, cooling devices have to work in order to lower the temperature and guarantee the availability of IT devices, which will consume considerable amount of power too.

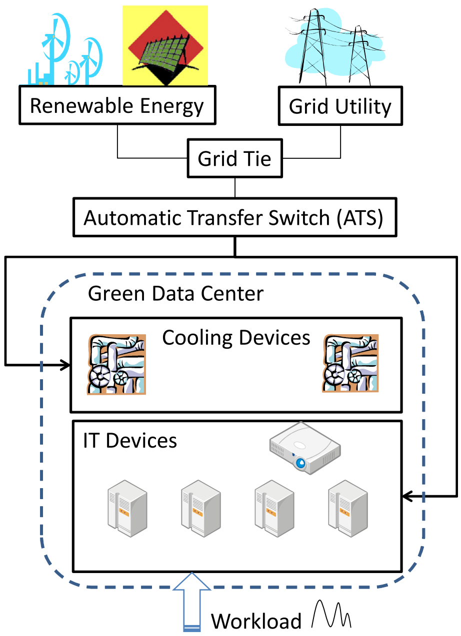

Fig. 1. Architecture of the green datacenter powered by hybrid energy.

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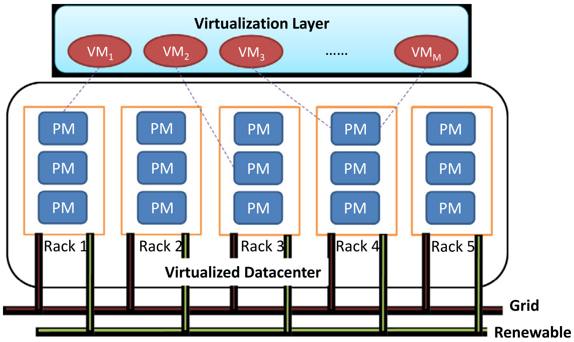


Fig. 2. Infrastructure of the virtualized datacenter.

3.2. Virtualized datacenter infrastructure

The infrastructure of virtualized cloud datacenter is illustrated in Fig. 2. The cloud datacenter consists of multiple physical machines (PMs), which are also called the underlying infrastructure. These physical machines are grouped and placed on different racks inside the room. Each rack will be connected onto the grid bus and the renewable bus, receiving the supply of both kinds of energy. When green energy is sufficient, the racks will be supplied by green power first. Grid energy is used only when the renewable energy is not enough to maintain the operation of the running devices.

Different applications are deployed in one or multiple VMs which are running above the underlying PMs. In Fig. 2, a VM and the PM it resides on are connected by a dotted straight line. Notably, a physical machine could host multiple VMs serving for arbitrary applications. In this paper, we assume these VMs are receiving transactional workloads, which consume CPU as the main resource.

4. Problem formulation

This section defines the necessary variables and notations used throughout this paper, and formulate the overall optimization problem we need to solve in following sections.

4.1. Physical machines and virtual machines

There are N heterogeneous physical machines in the virtualized cloud environment described above, and the available CPU resource capacity of PM i is denoted as Φ_i. Here, the following discussion is based on the assumption that other resources are constantly consumed independent of workload variation.

The entire environment is hosting M kinds of different applications, deployed on M different VMs. Here, we denote the jth VM as VM_j. Then, we use a binary integer x_j to represent which PM is hosting VM_j, indicating the current VM placement situation on the physical machine. Since the workload varies as time elapses, the CPU capacity allocated to each VM might be changed according to the VM placement scheme. We denote as ϕ_i as the currently assigned CPU capacity to VM_j and d_i as the demanded CPU capacity of application j at the current time slot.

4.2. Power consumption of IT and cooling devices

According to prior relevant study, modern CPUs can dynamically adjust their voltage and frequency by using DVFS techniques and thus could be operated at different speeds. Here, we adopt a simple model which has been proved very useful in modeling power consumption since other components activities correlate well with CPU activity [27]. Denote p_i as the power consumed by PM i per time epoch, and p_i^{MAX} as the power consumed by PM i when it is activated and fully utilized. Then, we use the following power model for calculating the power consumptions of computing nodes:

$$p_i = cp_i^{MAX} + (1 - c)p_i^{MAX}\theta_i \tag{1}$$

where θ_i is the CPU utilization of PM i, and c is the ratio of the power consumed by a physical machine in idle state over in full utilized state, which is usually a constant [28].

Considering that the power consumed by cooling devices is also significant and non-ignorable for today's large datacenters [29], we also incorporate the cooling power cost into the model, which might be directly affected by temperature. Modern datacenters usually leverages multiple cooling approaches [16], including air economizer, water economizer and traditional chiller plant. Here, we consider a cooling system consisting of two approaches: air economizer and traditional CRAC (Computer Room Air Conditioning) unit. CoP (Coefficient of Performance) is usually used to characterize the efficiency of the cooling system, which is the ratio of provided cooling amount to electrical energy consumed to do the cooling. For outside air cooling, the cooling power depends on the outside air temperature and also the target room supply temperature. For water-cooled CRAC system, the CoP is independent of the outside air temperature and depends only on the supply temperature. As an example, here we use the CoP model of HP Labs Utility Data Center which has been used widely in prior studies [14–16,18]. To sum up, according to explanations in [18], the CoP can be modeled as:

$$CoP = \begin{cases} \frac{1}{k(T_{sup} - T_{out})}, & \textit{when } T_{out} \leqslant T_{sup}, \\ 0.0068T_{sup}^2 + 0.0008T_{sup} + 0.458, & \textit{otherwise}. \end{cases} \tag{2}$$

where T_{sup} is the target room supply temperature, T_{out} is the outside temperature, and k is a factor that depends on the difference between outside air and target temperature, which decreases with the increase of the difference between T_{sup} and T_{out}. Eq. (2) means that the datacenter uses air economizer when $T_{out} \leqslant T_{sup}$ and CRAC cooling when $T_{out} > T_{sup}$.

Combining the power of both machines and cooling units, the total power consumed by the whole datacenter can be computed by:

$$p_{DC} = \left(1 + \frac{1}{CoP}\right) \cdot \sum_{i=1}^{N} p_i \tag{3}$$

Since high environmental temperature is usually considered as harmful for the datacenter, and a huge electrical energy amount consumed by IT devices will be transformed into heat, we also exploit and incorporate thermal-aware considerations into the VM migration decision processes. The power issued by functional devices will be dissipated in the form of heat, and thus the power consumption of a node will make the temperature increase. According to prior studies [24], the vector of inlet temperatures T_{in} can be modeled as

$$T_{in} = T_s + D \cdot p \tag{4}$$

where T_s is the vector of supplied air temperature, D is the heat transferring matrix, and p is the vector of power consumption.

The purpose of using a temperature-aware strategy is to decrease the temperature of hotter servers so that the cooling power consumption can be reduced. To achieve this goal, we should try to balance the load on different PMs to make the utilization of all the physical nodes subject to proportional relationship. We denote a safe outlet temperature for the servers to be T_{safe}, and the outlet temperature of the server with highest temperature to be T_{server}. In order to lower temperature of servers to a safe level, the output temperature of cooling devices should be adjusted by $T_{adj} = T_{safe} - T_{server}$. After the adjustment, the resulted output temperature should be $T_{new} = T_{sup} + T_{adj}$. Hence, the CoP could be determined by T_{new} and T_{out}, which directly affects the cooling power consumption [30].

4.3. Operational costs

According to the previous description of the datacenter, in order to reduce energy consumption, a physical node can transit to inactive state (e.g. sleep mode, hibernate mode or shut off). Hence, we denote a_i to be the value indicating whether PM i is in active state. We also include into the objective the operational costs during the procedure of migrating VMs from one PM to another dynamically, due to certain adaptation actions. Hereafter, the cost for activating a physical node from inactive state to active state is denoted as c^A, and the cost for migrating a VM from one node to another is denoted as c^{MIG}. To activate a physical machine or to migrate a virtual machine will incur some wakeup delay or migration delay. In Section 6, the delay time will also be incorporated in the experiments.

4.4. Optimization problem

For resource providers of the datacenter, the ultimate objective is aiming at the overall net revenues of serving the applications jointly as well as the consumed power and operational cost. Generally, the profits by serving the deployed applications should be determined by the actual measured QoS level and the user-required QoS level specified in SLAs. We use the allocated CPU capacity to a certain application to measure its QoS level. We denote the desired CPU demand of APP j according to the SLA as d_j, and the allocated CPU capacity for APP j as ϕ_j. Assume that we can obtain the cost model function for a certain APP j, denoted as $\Omega^j(\bullet)$, from which we can get the achieved profits by computation.

Due to the dynamic adaption process, the VM migration decisions are made in constant intervals. We denote τ to be the length of one time epoch. If the current interval is denoted as time epoch t, the optimization objective for epoch $t+1$ is to optimize the overall profits by running the applications subject to the constraints of SLA while minimizing the total cost, including energy and operational cost. The decision variable in the optimization problem is the configuration vector of virtual machine placement, denoted as follows:

$$X = (x_1, x_2, \ldots, x_j, \ldots, x_M) \tag{5}$$

where x_j is the number of PM which currently hosts VM j.

Then, the objective described above can be formulated as

$$max\sum_{j=1}^{M}\Omega^{j}(d_j,\phi_j) - c^{P}\cdot p_{DC} - c^{A}\cdot\sum_{i=1}^{N}max(0,a_i(t+1)-a_i(t)) - c^{MIG}\cdot\sum_{j=1}^{M}(x_j(t+1)-x_j(t)) \tag{6}$$

where the first term is the summarized profits by finishing workloads, the second term is the power consumption in the next time epoch, the third term represents the cost of activating a PM, and the fourth term is the total cost of migrating VMs.

Based on the previous description, the restraints of the optimizing problem could be formulated as follows:

$$\sum_{x_j=i}\phi_j \leqslant \Phi_i\cdot a_i \tag{7}$$

$$0\leqslant \phi_i \leqslant d_j,\ j=1,2,\ldots,M \tag{8}$$

$$a_i\in\{0,1\}, x_j\in[1,N] \tag{9}$$

where Eq. (7) restrains that the capacity allocated to all VMs cannot be more than the summarized CPU capacity of PM i and Eq. (8) expresses the allocated capacity of each VM would be no more than its original demand. Eq. (9) depicts the bounds of involved variables.

For clarity, the parameter notations used hereafter in this paper are listed in Table 1.

5. Resource and energy management approaches

In this section, we present several resource and energy management approaches, including heuristic methods and also the hybrid optimization algorithm we design in this research.

5.1. Dynamic Load Balancing (DLB)

The *DLB* strategy is aiming at dynamically balancing the workload on different physical machines. Thus, the utilization of each PM is periodically checked. If the utilization of a certain PM is beyond the predefined upper threshold, a migration instruction will be triggered to migrate some VMs on this machine. This process repeats until its utilization is reduced below the threshold. In this way, the number of overloaded machines will be reduced as much as possible.

5.2. Dynamic VM Consolidation (DVMC)

In some cases, balancing all the loads across PMs is not always the best method if we consider the energy consumption of the servers. Virtual machines could be consolidated to several PMs when they require less resource. Based on this concept, the *DVMC* strategy aims at consolidating VMs onto a part of the PMs, so that the other part of PMs could be turned into sleep state to save more power. Hence, two thresholds are predefined, including both the upper threshold and the lower threshold. It will trigger the consolidation process once the utilization of a certain PM comes below the lower threshold. All of the VMs currently on the underutilized PM will be distributed onto other machines. In this way, under-utilized machines could be released and turned into sleep, which helps to save unnecessary power consumption.

5.3. Joint Optimal Planning (JOP)

This section presents our approach based on joint optimal planning, which optimizes the VM migration strategy towards maximizing the utilization of green energy and keeping the profits acceptable.

Table 1
Parameter notations.

Symbol	Description	Symbol	Description
τ	The length of control interval	x_j	The number of PM which hosts VMj
N	Number of physical machines	ϕ_j	The CPU capacity allocated to APP j on a certain PM
M	Number of applicationsvirtual machines	d_j	The maximum CPU capacity demanded by APP j
Φ_i	Available CPU capacity of PN i	U_j^{max}	The maximum profit bought by APP j in a time slot
a_i	1 if PN i is now in active state, θ otherwise	$\Omega^j(\bullet)$	The revenue function of APP j
p_{DC}	The power of the entire datacenter	T_{sup}	The temperature of supplied air
p_i	The power of PM i	T_{safe}	The predefined safe outlet temperature
θ_i	The CPU utilization of PM i	T_{out}	The outside temperature
c^P	Power consumption cost	CoP	Coefficient of performance
c^A	PM activation cost	D	Matrix of heat distribution
c^{MIG}	VM migration cost	T_{in}	The vector of inlet temperature
	Decision variable	T_s	The vector of supplied air temperature
X	The configuration vector of VM placement	p	Power consumption vector of PMs

5.3.1. Solar energy prediction

Since the goal of our approach is to utilize green energy as much as possible, it's necessary to predict the production amount of renewable energy beforehand. We adopted a k-nearest neighbor (k-NN) based algorithm to predict the solar energy generation for the next day. On the basis of the k-NN model, we calculate the distances of samples and the prediction point, arrange them in the distance ascending order, select k points closest to the point and pick up the distance values corresponding to the k points, and use a distance weight function to determine the distance value of each of the solar radiation values. The weight of the ith neighbor point is calculated as follows:

$$w_i = \left(\frac{1}{d_i}\right)\left(\frac{1}{d_1}+\frac{1}{d_2}+\cdots+\frac{1}{d_k}\right) \tag{10}$$

where d_i is the distance value between the current point and the ith neighbor. Then, the forecasted value can be obtained by multiplying the k radiation values by their weight coefficients respectively and finding the sum of the weighted radiation values.

Fig. 3 shows the actual measured and predicted values for the solar energy generation for a day (24 h, 1440 min) in October, 2013, measured in Qinghai University, Xining, Qinghai Province of China. Specifically, Fig. 3(a) is an example of sunny day prediction, where the accuracy is much better than the cloudy day shown in Fig. 3(b). According to our analysis, the allowed absolute percentage errors (AAPE) of 97.01% of the data points are less than 30% for the best day, and 76.11% for the worst day. We are using weather forecast information to match the similar weather day in the historical database. Hence, the accuracy of the prediction method depends on the similar weather conditions in the recent past. If the historical data of the similar day is not available, the prediction accuracy will be lower. The detailed description of the prediction approach can be found in our prior work [35].

5.3.2. Stochastic search based on genetic algorithm

As defined in the previous section, the objective of dynamic virtual machine migration is to study the best VM placement scheme to optimize the total revenue defined in Eq. (6) in the next time epoch subject to the constraints. The space of configuration vector will be traversed and the one leading to highest objective value will be determined. Here, we use the stochastic search to find the most close-to-optimal results, where Genetic Algorithm (GA) is employed to perform the optimization.

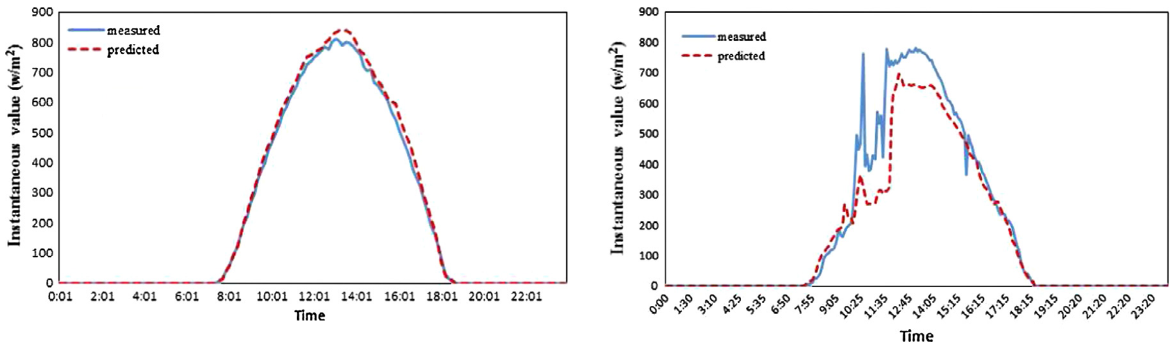
For this problem, the decision variable is the vector of VM placement, which can be denoted as $X = (x_1, x_2, \ldots, x_M)$. The objective function defined by Eq. (6) could be used as the fitness function. It is functional in measuring the quality of a certain solution. Hereafter, the fitness function will be denoted as $F(X)$. The procedure of genetic algorithm includes initialization, selection, reproduction by mutation and crossover and finally terminates until the number of generations reaches to a predefined level.

6. Experiment and simulation

In this section, we have conducted some results of experiments to investigate the effectiveness of the proposed strategy. First, we introduce the parameter settings of the simulated prototype testbed. Then, experimental results are shown and analyzed, including total power consumption, total revenue, physical machine state and cooling power consumption.

6.1. Environment settings

For establishing a prototype testbed, we used C#.NET to develop an event-driven simulation environment, which can simulate the workload variation, application behaviors, task completion status, and energy consumption. For the following



(a) Sunny (b) Cloudy

Fig. 3. Example of solar energy prediction.

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experiments, we have established a virtualized datacenter that contains 40 identical servers, each with a CPU capacity of 1500 MIPS. The power consumption will be calculated according to the model presented in Section 4.2, where p_i^{MAX} is set to 259 W according to the SPECpower benchmark [31] and c is set to 66% according to [28]. Then a physical machine consumes about 171 W with no workload running on it, and consumes up to 259 W when it's fully utilized.

Upon the underlying physical infrastructure, we simulated 100 heterogeneous VMs hosting different kinds of applications. The workload and CPU demand of each VM varies as time elapses. The initial demand, maximum demand and the demand variation speed of the VMs are set randomly according to the uniform distribution, simulating the independent fluctuation of different application workload types.

The detailed parameter settings for deployed applications are shown in Table 2, including the upper bound and lower bound of CPU capacity as specified by SLA and the utility brought per request. The summarized CPU demand of all the workloads is shown in Fig. 4, which illustrates the intensity variation of the incoming load. We can see that there are two obvious peaks in the morning and right afternoon respectively, which shows the coincidence with people's working time, wherein there is a small dropdown during noon time.

For each application, a non-linear revenue function is used to specify the revenue incurred when the allocated CPU capacity is set to a given value. When the allocated capacity goes beyond the SLA-based upper bound, the gained revenue will be relatively constant. Once the allocated capacity falls below the predetermined lower bound, the revenue drops down linearly. Typical examples of three different applications are depicted in Fig. 5, from which we can see that the revenue does not drop too fast if the allocated capacity is between the lower bound and the upper bound. It shows the elasticity of the applications in a certain range.

Table 2
Parameter settings.

Application	APP 1	APP2	APP 3
Lower bound	50	40	30
Upper bound	90	60	70
U_j^{MAX}	100	60	80

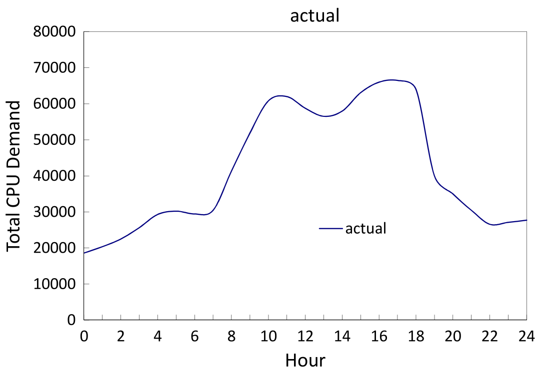

Fig. 4. The intensity variation of incoming workloads.

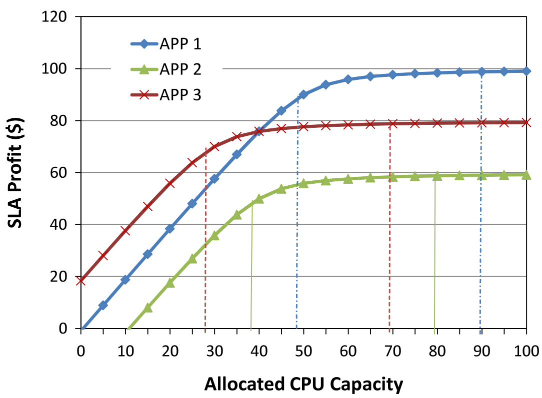

Fig. 5. Example revenue functions of three applications.

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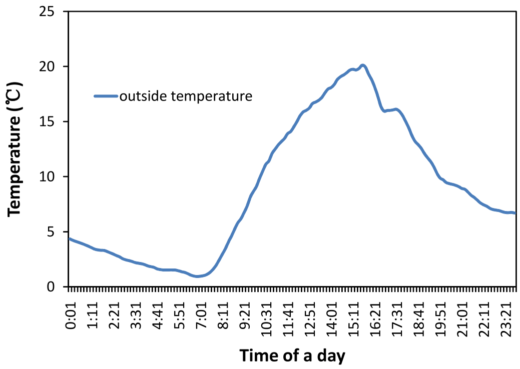

Fig. 6. Variation of the outside temperature in a day.

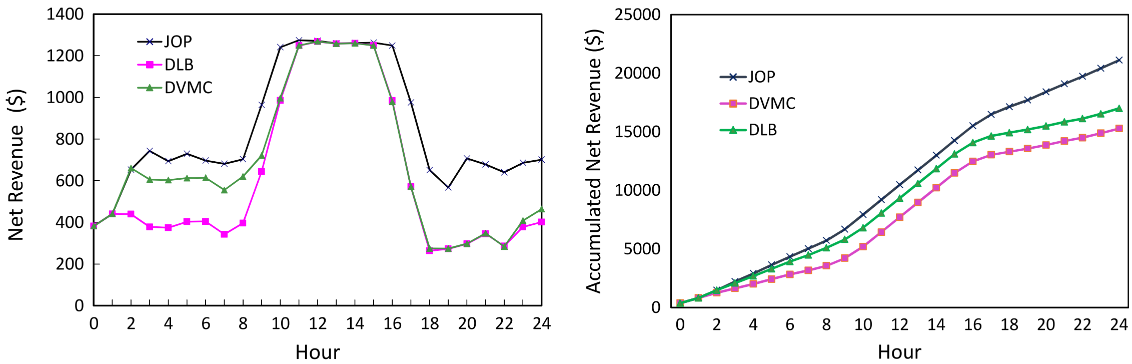

Fig. 7. Net revenue variation under three different strategies.

During the experimental period, a VM migration decision is made in every 60 min (1 h). In accordance with [32], we set the cost of energy per kW h (c^P) to \$0.08. Besides, we set the activation cost of a single server (c^A) to \$0.00024 according to [33], which takes the energy cost for reboot into consideration. We also set the cost of migrating virtual machines from one sever onto another server (c^{MIG}) to \$0.00012 according to [34]. Moreover, to simulate the delay effects in reality, we set the VM migration time to 5 s, and the wakeup time of a sleeping physical node to 15 s. The simulation time of the entire experiment is 1440 min in total, which simulates a 24-h whole day effect of system running. Besides, the outside temperature data used in our experiments is the air temperature in a day of 4th October, 2013, recorded every 10 min in the campus of Qinghai University, Xining, Qinghai Province, China. The variation of the input temperature is as shown in Fig. 6.

6.2. Results

6.2.1. Global net revenues

During the experiments, we have evaluated net revenues as a main performance metric, which considers both revenues brought by meeting SLAs of applications and also the summarized cost. The three different strategies have been simulated respectively. Fig. 7(a) shows the variation of net revenues by hour and Fig. 7(b) shows the total accumulated revenue throughout 24 h.

By observing the results, we can see that the net revenues under the *JOP* strategy can be kept relatively high compared to other strategies. When the green energy is sufficient near noon, the three strategies achieve similar levels of net revenue. However, in other time intervals, the *JOP* method exhibits remarkable advantage over the other two strategies. Relatively, the *DVMC* approach behaves better than *DLB* since it is prone to consolidate multiple VMs onto fewer machines, so that more energy could be saved. According to the results of Fig. 7(b), the *JOP* strategy could bring 38.2% and 24.2% more accumulated revenues than *DLB* and *DVMC*, respectively.

6.2.2. Power consumption

To further investigate the behavior of our approach, we have recorded the power consumption situation under the *JOP* strategy in detail. The evaluation results are illustrated in Fig. 8, which show the comparison of the detailed power consumption breakdown under the three different kinds of strategies. Here, the power supply is hybrid including both brown energy

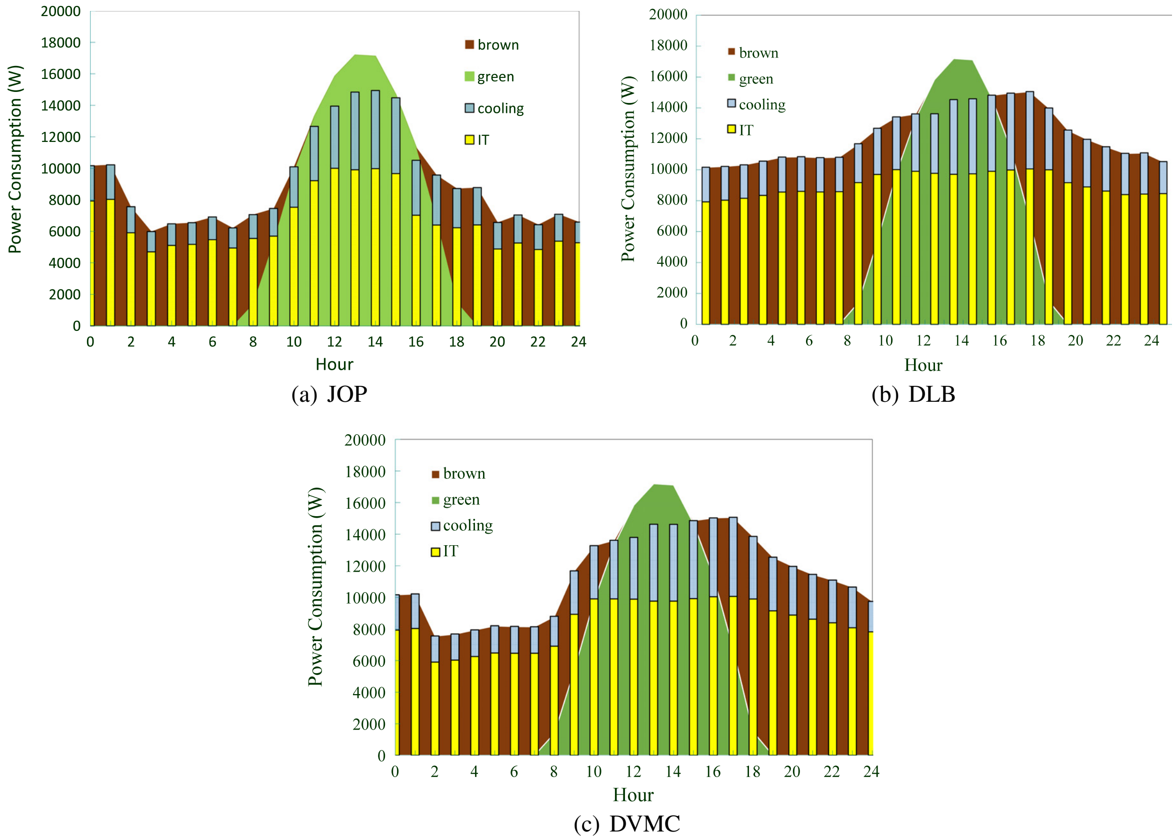

Fig. 8. Power consumption under three different strategies.

and green energy, as studied in Section 3.2. On the other hand, the power consumption also includes two main parts: IT devices and cooling devices. We can see from the results in Fig. 8(a) that the *JOP* strategy could follow the variation of the green energy supply amount well. When there is no renewable energy available, it attempts to compromise the SLAs of the applications, leading to more brown energy savings. When the renewable energy becomes sufficient, both the IT devices and cooling devices consume much more power, as long as the total consumption does not exceed the capacity of the power supply. Notably, the cooling power consumption becomes extremely high between 13:00 and 15:00, because the temperature outside rises higher than the target supplied temperature, and thus the CRAC units have to start working. In other time intervals, using the air economizer is enough, since the outside temperature is low. It is promising that the temperature variation is correlated with the variation of solar energy generation amount to some extent, which brings more opportunities for the study of co-scheduling energy supply and energy consumption. In comparison, the *DLB* strategy is prone to stably consume much more power over time, as shown in Fig. 8(b); the *DVMC* strategy tries to consolidate VMs to reduce energy but does not follow the dropdown of the green energy when approaching night time, as shown in Fig. 8(c). By looking into the details of the power consumption from different sources, the reason why *JOP* can achiever higher revenues would be easy to understand.

6.2.3. Management of physical nodes

In this subsection, we plot the number of active servers under the three different strategies, as shown in Fig. 9. It shows that our approach can catch up with the variation of renewable energy supplies by adding or reducing the number of active servers. When using *DLB*, all of the physical machines stay active to balance the overall workload of the whole system. Under the *DVMC* strategy, VMs could be consolidated together onto a small number of physical machines, so that the active PMs become significantly fewer. However, this strategy still uses many PMs in the latter part of the day, since it does not try to trade-off profits and costs. In contrast, the *JOP* strategy attempts to dynamically manage the status of physical machines towards the predetermined objective, which make the active PMs count also follows the variation of renewable energy generation amount.

6.2.4. Cooling energy consumption

Moreover, we also examine the cooling energy consumption amounts under the three different strategies. Fig. 10 shows the results. It can be seen that the other two strategies except *JOP* keeps leading to high cooling power consumption until

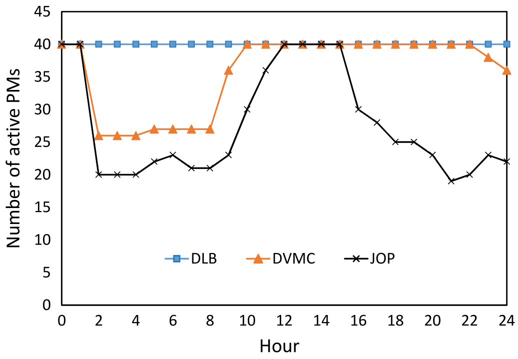

Fig. 9. Variation of the number of activated physical machines.

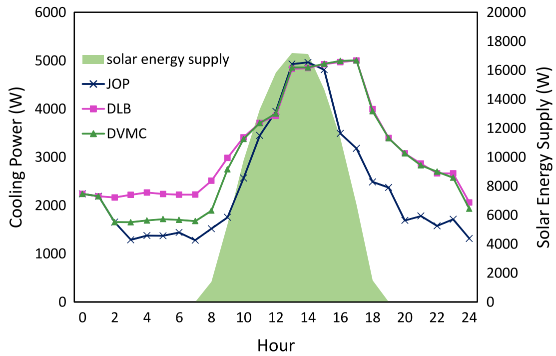

Fig. 10. Power consumed by cooling devices under three different strategies.

after 18:00, while *JOP* captures the solar energy variation much better. In average, the *JOP* strategy saved 37.6% power than *DLB* and 36.8% power than *DVMC* after 18:00 respectively. This is because that according to the prediction of solar energy generation, the *JOP* strategy could proactively learn the trends of renewable energy amount, and thus optimize better the configuration vectors to instruct the VM migration decisions.

7. Conclusion

In this paper, we studied the VM migration approaches facing the environment that hybrid energy supplies are used for target datacenters, including grid energy and renewable energy. We first describe the system architecture of such datacenters, and we then explored the inside infrastructure of the virtualized datacenter. We further defined and formulated the optimization problem with a clear objective of cost reduction. Considerations about temperature impacts are also integrated into the proposed framework, considering mixed cooling methods, including both CRAC and air economizer. We evaluated three different strategies to migrate VMs across the physical machines dynamically, one of which was renewable-energy-aware and thermal-aware. Especially, the *JOP* strategy we proposed used stochastic search to find out the close-to-optimal solution of the defined problem. Finally, experimental and simulation results showed the effectiveness of our green-aware VM migration strategies. In addition, the total revenues, PM states, and cooling power consumption were also investigated, which showed that the proposed strategy could result in more net revenues by trading-off the SLA profits and brown power consumption as well as other costs. By comparing the three different approaches, our strategy exhibited the advantages over the other two approaches, since it utilized green energy more efficiently. As a part of ongoing work, we are planning to study and explore the detailed thermal impact among machines and racks, and also other renewable energy types.

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