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Towards green cloud computing: Migrate virtual machine identification and evaluation

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ABSTRACT

Based on the analytical hierarchy process proposed a virtual machine migration evaluation model for green cloud computing. Through the establishment of index system of virtual machine CPU task usage, the construction of pair-wise comparison matrix and the adoption of five-point rating scale, the model is able to evaluate the liability of migration and resource usage of the virtual machine. By using relevant attributes of virtual machine, an attribute clustering based collaborative filtering method is applied for the calculation of similarities between virtual machines and the generation of migrate recommendation. Finally it can help the cloud server administrators for choosing the optimum green virtual machine migration scheme to save power consumption of cloud server cluster. Experiments show that, the proposed model and method is feasible and has the vital significance to the green cloud computing.

KEYWORDS

Green cloud computing; Virtual machine migration; Analytical hierarchy process; Collaborative filtering.

INTRODUCTION

Cloud computing itself maximizes the usage of server resource, therefore it avoids the resource waste of traditional computing mode. But recently, the contradiction between the Cloud computing and the environmental protection is gradually increasing. Because the Cloud computing services and the computing infrastructure is expanding and developing, it is often questioned whether cloud computing is a cloud of pollution. Green Cloud computing focuses on alleviating the negative environmental impact of the Cloud computing.

In green Cloud computing, influencing factors are concerned which has great impact on ecological environment for energy saving and environment protection reason. Such factors mainly include power consumption, space occupied and heat emission. In recent years the green cloud computing has been studied by many researchers. Paper [1] proposed the green energy-saving strategies for cloud computing platform. Paper [2] presented an automatic management framework of cloud infrastructure to reduce energy consumption of Cloud server. However, the best way to reduce power consumption and heat dissipation is to limit the usage of Cloud infrastructure. More specifically, power off Cloud servers when the usage of which is low. But it would be a challenge to choose switch off a server. The cloud server is usually a host machine of aggregated virtual machines (VM). So before switch off the power, all VMs need to be analyzed to determine which operates effectively and actively. Then after migrate the effective and active VMs to other stable cloud server. It is feasible to turn off the original host to reduce energy consumption. However, to determine whether a VM is effective and active is equally challenging. But the active VM can be obtained from analyzing the characteristics of its behavior and usage on a VM task usage perspective. Because Cloud computing can enable more energy-efficient use of computing power, especially when the computing tasks are of low intensity or infrequent [3]. Although utilizing task usage information to evaluate an active VM is feasible, to decide which VM to migrate is still a problem. Therefore, this situation should be defined as a decision-making problem.

The analytic hierarchy process (AHP) [4] is a decision-making method designed to help solve the complex problem with multiple criteria in many application fields. Such method is effective and practical for the complex and unstructured decision problem [5]. Thus to solve decision-making problems, the AHP method has been widely accepted in many application fields [6,7]. Find out the active VM with high stability of a Cloud server and migrate it through the AHP method will provide great convenience for Cloud system administrators.

Collaborative filtering is designed to generate recommendations for users of certain application domain. For example, [8] proposed a collaborative filtering algorithm based on spatial clustering, then it divides the recommended process into two stages of offline and online. Cheinshung Hwang[9] proposed the fuzzy set theory based clustering collaborative filtering algorithm for the prediction of web pages. Therefore, by uniting collaborative filtering method with the results of the AHP method, similarity between the migration VM and other virtual machine is able to be obtained. Then, it is able to provide VM with high similarity for recommendation of migration to the Cloud system administrator.

This paper proposes an AHP model for processing influencing factors between VM migration decisions and task usage. Cloud administrators then can determine the importance of criterion for the task resource usage of pair-wised comparison matrix. Then alternative migration VMs are prioritized or weight calculated. For determination of the VM to migrate onto stable host, AHP model is depicted based on the CPU usage as it is the key factor associated with task usage. By referencing attribute clustering based collaborative filtering, a model is proposed to provide VM migration recommendation by using the results of AHP model for the system administrator. Finally, the system administrator switch off the host machine according to the recommendation so as to achieve the purpose of energy saving.

MIGRATE VIRTUAL MACHINE EVALUATION MODEL

Evaluation index system

Three basic steps of AHP are applied to solve the decision problem is: first, index system is established for analyzing the relationship between factors of the system. Pair-wised comparison matrix is created for evaluating the importance of each element on same layer towards the above layer; second, judgment matrix is formed to calculate relative weights of elements being compared. Then, consistency of judgment matrix is checked; third, global weights of all levels are calculated. Finally, total ranking of each scheme towards overall goal is obtained.

Establishing hierarchy of index system is based on the selection of impact factors has certain influence on the evaluation results. And the process of establishing the index system is such an evaluation activities through a series of indicators. Index system refers to a scale set for comprehensive measurement of an evaluation object. The scale set is composed of a series of indexes. Comprehensive evaluation index system is a widely accepted method to analyze systems in the social, economic and management science fields. Evaluation system often has a hierarchical structure including goal and criterion layers to form a multi-level evaluation system.

Building hierarchy for VM migration evaluation can be considered as an evaluation model for VM migration. Therefore from the perspective of CPU usage, CPU usability and cyclicity are the two main performance criterion. Therefore, sub criterion of CPU usability can be obtained such as the average CPU rate, maximum CPU rate, cycle per instruction and task duration. Figure 1 illustrated the index system of VM migration evaluation.

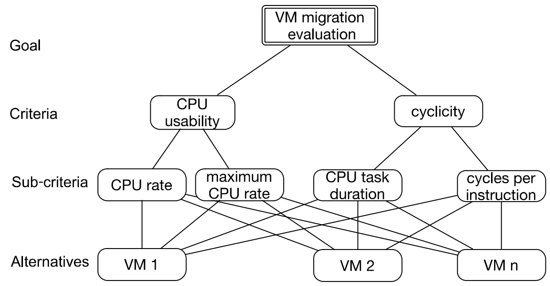

Figure 1 : Migrate VM evaluation index system.

Form Figure 1 the most suitable VM for migration can be obtained. However, for one VM, single task usage information cannot represent a definite behavior, because task usage of a VM consist of arbitrary task vector. Therefore, it is needed to analyze the overall task usage of VM to select the proper representative task usage information. The second hierarchy then is depicted to select the proper representative task usage information of one VM. Figure 2 is the index system of overall task usage evaluation of one VM. Compared with Figure 1, Figure 2 introduces the task validity as evaluation index to depict the time interval between task execution and current.

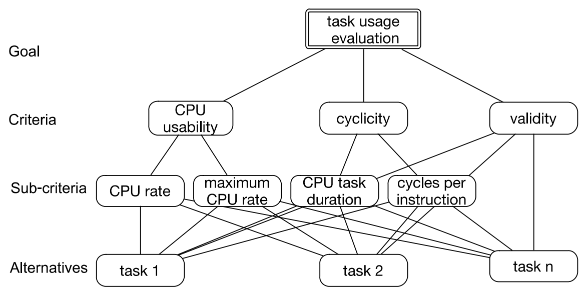

Figure 2 : Task usage evaluation index system.

Pair-wised comparison matrix

When the establishment of index system is complete, all factors that influenced VM migration shall be analyzed by constructing pair-wised comparison matrix to judge criterion weights and check the consistency of judgment matrix.

TABLE 1 : Criteria and sub-criteria.

goal	criteria	Sub-criteria
Node evaluation	CPU usability(C1)	CPU usage(C11)
		Maximum CPU usage(C12)
	Cyclicity(C2)	CPU task duration(C21)
		Cycles per instruction(C22)
Task usage evaluation	CPU usability(B1)	CPU usage(B11)
		Maximum CPU usage(B12)
	Cyclicity(B2)	CPU task duration(B21)
		Cycles per instruction(B22)
	Task validity(B3)	

Before the comparison, all factors should first be analyzed. For virtual machines running in the cloud cluster, if the average CPU rate is high, then the cloud services consume high CPU resources. If the virtual machine is moved to another physical machine, the original host machine can be switched off. Then, the migration of such VM can save electric energy effectively. The same rule can also be applied to the situation when maximum CPU rate is low.

On the other hand, if the CPU task duration is short, it indicates that a VM CPU is dispatching frequent tasks. Otherwise, long CPU task duration indicates an infrequent tasks scheduling, such VM needs to be migrated. Cycles per instruction describes the instruction type that CPU executed. Once the cycles per instruction is short, that may indicate the instruction is a conventional instruction including operation instruction, short instruction, and short data operation instruction. Typically, those instructions are used only for calling register. Then, we can migrate the VM for long-term operation. A long cycle per instruction indicates the co-processor is required for big data operation or conducts abnormal control etc. More precisely, the operation duration is not long, and even soon the VM will be terminated. It is unnecessary to migrate.

From Figure 1 and Figure 2 we can summarize the criteria and sub-criteria that we've identified as being important in the VM migration decisions. Table 1 is the result.

Then we are able to develop the pairwise comparison matrices to determine the criteria and sub-criteria weights. The weights for all the pairwise comparison matrices were then be computed. Table 2 shows the result global weights of all criteria.

For all VMs in alternatives layer, the metrics value of VMs toward sub criterion is obtained by summing up the multiplication result between data and the weight value of such sub criterion. Furthermore, VM migration evaluation results can be obtained by summing up the multiplication result between such metrics value and weight value of criterion. Finally, the most suitable migration VM is determined once all VMs are calculated and prioritized.

TABLE 2 : Pair-wised comparison matrix.

C_1 C_2 weight 1 5 0.8333 1 0.1667	C_1 C_{11} C_{12} weight C_{11} 1 7 0.7292 C_{12} 1 0.1042
CR=0	CR=0
C_2 C_{21} C_{22} weight C_{21} 1 5 0.1389 C_{22} 1 0.0278	B_1 B_2 B_3 weight 1 7 1/2 0.3631 1 1/7 0.0664 1 0.5706
CR=0	CR=0.0519
B_1 B_{11} B_{12} weight B_{11} 1 6 0.3112 B_{12} 1 0.0519	B_2 B_{21} B_{22} weight B_{21} 1 6 0.0569 B_{22} 1 0.0095
CR=0	CR=0

For cloud system administrators, migration VM is now identified according to defined weight value. As the VM in a Cloud cluster abundant in numbers, deciding only one VM to migrate is insufficient for achieving energy efficiency. It is necessary to find out other migration VMs. Such migration VMs can be obtained by calculation of similarities between the identified VM and all other VMs. Then, we can recommend all VMs that have high similarity value to system administrators, for reducing the energy consumption of Cloud server cluster and the manual workload. Then collaboration filtering is needed.

VIRTUAL MACHINE SIMILARITY CALCULATION

Attribute clustering based collaborative filtering

According to the above statements, if the task occupied high average CPU rate, maximum CPU rate, short cycles per instruction and long task duration, the VM is suitable for migration. So given the alternative cluster of VM migration.

Definition

A cluster C is defined as the Alternative Cluster of Virtual Machine Migration (ACVMM), if C with VMs that has task usage data that composed with high CPU rate, maximum CPU rate, cycles per instruction and long task duration.

Traditional collaborative filtering algorithm generates recommendations by the calculation of nearest neighbor of target users. Item-based collaborative filtering first calculates the correlation between items. Then it predicts the users score towards unrated items by referencing rating of correlated items [10]. Therefore, it is able to predict the user interest by analyzing the cluster commonalities. Moreover, clustering is able to partition users with similar interest into a same cluster [11] and predict the trend of users interest based on analysis of sub cluster. This paper assumes that users are the Cloud cluster system administrators. The collaborative filtering algorithm proposed here is dedicated to recommending ACVMM to system administrator according to the result migration VM obtained from AHP method. VM activity is measured by data of computing tasks of each virtual machine. Stable VM has higher frequency of usage, which needs to be migrated. Unstable VM has lower frequency of usage, which needs to be resided on the host machine. At this time, it is able to measure activity of VM by using task resource usage data to each virtual machine. Then, rating table is required to map the raw data for applying collaborative filtering. Finally, ACVMM is able to be obtained by utilizing clustering method and rating table.

Virtual machine similarity judgement

For clustering convenience, we introduce an VM attribute space to summarize the VM rating score into number of feature clusters, which denoted as $\Omega = A_1, A_2, \cdots, A_k$. Where k is the number of attributes of a VM. For some VMs, however, a specific attribute may have multiple attribute values. Therefore, this paper adopts the single attribute to obtain similarity of a VM on a particular attribute. Then sum all the similarity of attributes, and then calculate the average similarity, the similarity between VMs. For example, attributes space of the VM I_1 and I_2 is denoted as $A_1 = \{a_{11}, a_{12}, \cdots, a_{1k}\}$. Therefore, we can get the VM attribute matrix $n \times k$ from attribute A_1 as shown in Table 3.

TABLE 3 : VM attributes matrix.

	a_{11}	a_{12}	…	a_{1j}	…	a_{1k}
I_1	1	0	…	1	…	0
I_2	0	1	…	0	…	1
…	…	…	…	…	…	…
I_i	1	0	…	1	…	0
…	…	…	…	…	…	…
I_n	0	1	…	0	…	1

In Table 1, column k indicates attribute A_1 has k values, while row n indicates the number of VMs. 1 and 0 represents whether A_1 attribute of the VM conform to the attribute values of all other VMs. 1 is conform to, 0 is not conform to.

The sample space then is reduced, now we need to choose from which a VM needs to be migrated. After VM attribute matrix is constructed, we are able to calculate the similarity for further measurement of similarity degree between VM I_1 and I_2 toward attribute A_1. A set of feature vector is then formed with respect to the conformity value of a VM towards certain attribute. For example, the feature vector of user I_1 and I_2 toward attribute A_1 is depicted as $\overrightarrow{I_1A_1} = \{i_1a_{11}, i_1a_{12}, \cdots, i_1a_{1k}\}$ and $\overrightarrow{I_2A_1} = \{i_2a_{11}, i_2a_{12}, \cdots, i_2a_{1k}\}$.

Then the attribute similarity of I_1 and I_2 toward attribute A_1 can be represented as:

$$S_1 = sim(I_1A_1, I_2A_1) = 1 - \frac{\overrightarrow{I_1A_1} \oplus \overrightarrow{I_2A_1}}{K} = 1 - \frac{\sum_{i=1}^{k} \overrightarrow{I_1a_{1i}} \oplus \overrightarrow{I_2a_{1i}}}{K} \quad (1)$$

Where $sim(I_1A_1, I_2A_1)$ is the similarity, $\overrightarrow{I_1A_1} \oplus \overrightarrow{I_2A_1}$ is the attribute value with no commonality between I_1 and I_2 toward A_1. Such attribute value is capable for the generation of probability value of certain attribute of the VM after XOR operation. Then the attribute value, with no commonality, is summed and divided by K . The result depicts the incoherence degree towards A_1. Note K is the total value numbers of A_1 .

Next, the average trust degree of similarity, $EA(sim)$, between I_1 and I_2 is calculated as:

$$\bar{S} = EA[sim(I_1, I_2)] = \frac{\sum_{i=1}^{m} sim(I_1A_i, I_2A_i)}{m} \tag{2}$$

Then, the expectation value of trust degree among all attributes is obtained to describe the mean value of similarity between VMs. m is the number of attributes used for such description.

Therefore, similarity between VMs can be obtained:

$$S = sim(I_1, I_2) = \frac{\sum_{i=1}^{k}(S_1 - \bar{S})}{\sqrt{\sum_{i=1}^{k}(S_1 - \bar{S})^2}} \tag{3}$$

It describes the similarity between VM I_1 and I_2. Where k is the total value numbers of A_1.

Similarity clustering

In this paper, we simply use the k-means algorithm for the VMs group analysis. Assuming dataset and cluster centroid is n dimensional vector, we repeat following two steps until the convergence:

Step 1: for each x^i, obtain the nearest centroid j and then mark it into different categories.

We need to assign x^i to cluster x^j for assign all points into its nearest centroid.

$$set\ c(i) = arg\ min \| x^i - vm^j \| \tag{4}$$

Step 2: updates the cluster centroid to the average value of all points, to determine the new centroid.

$$\begin{aligned} &set\ distance = d \\ &set\ clster\_center = EA(distance) \end{aligned} \tag{5}$$

Assuming there are n instances, thus the recommended collection is $R = \{VM_1, VM_2, ...VM_n\}$. After treated with K - means algorithm, the clusters can be described as $C = \{c_1, c_2, \cdots, c_j\}$. Where j is the total cluster numbers, c_i contains the VMs with high preference and interest similarity. The realization shows as follows:

STEPS :

Step1: searching n VMs within VM attribute matrix, depicted with collection $R = \{VM_1, VM_2, ...VM_n\}$;

Step2: randomly choosing j VMs. Setting their attribute data as the initial cluster centroid, depicted with collection $C' = \{c_{1'}, c_{2'}, \cdots, c_{j'}\}$;

Step3: empty j clusters, depicted with collection C ;

Step4: Perform the following actions on the rest of the VMs:

VM-clustering-algorithm

Input:

Cluster number, j;

Virtual machine attribute matrix, $n \times k$;

Output:

Clusters of matrix $n \times k$, C;

for each $vm_i \in R$ **do**

  for each $c'_j \in C'$ **do**

    $x_{i,j} = sim(vm_i, c'_j)$

  end for

  if $x \neq \varnothing$ **then**

    for $m = 1$ **to** x_{length} **do**

      $X = \max\{x_m\}$

    end for

9: **end if**
10: $c_i = X \cup vm_i$
11: $C+ = c_i$
12: **end for**
13: **return** *C*
Step5: calculate the mean value of all VMs in the new cluster and update the centroid;
Step6: repeat Step4 to Step5 until centroid is stable, output ACVMM clusters.

With VMs-clustering-algorithm, we can find the VMs that have highest similarity. For VM in ACVMM, if one VM has highest similarity with the to be migrated VM instance cluster, it also should be migrated when considering task factors such as CPU usage and CPU cycle. Thus we get lemma 1.

Lemma 1

For the virtual machine with highest similarity with the AHP defined virtual machine, it should be included in ACVMM.

EXPERIMENT

Ahp application in migrate virtual machine identification

The experiment data was sampled from task usage table part-00000-of-00500 of Google clusterdata-2011-1[12].

Before using AHP model, we adopt Liberatore's[13] five-point rating scale for rating each sub-factor of alternative VMs to reduce the time and effort in making pair-wise comparisons. Table 4 and Table 5 show the modified pair-wise comparison matrix of the such rating scale. The matrix was normalized to obtain relative weight value of each metric for measurement of experimental dataset. As can be seen from both tables, for CPU rate, Maximum CPU rate and Cycles per instruction attributes we use very-high, high, moderate, low and very-low to normalize the raw data according to their values. While, for task duration, we using very-long, long, moderate, short and very-short to normalize the raw data. Then, the weights of very-high, high, moderate, low and very-low are calculated, which are equal to 0.513, 0.261, 0.129, 0.063 and 0.034, respectively. The weights of very-long, long, moderate, short and very-short are calculated in a same manner. On the other hand, the attribute task validity is calculated in a same way with task duration.

TABLE 4 : Five-point rating scale(a).

scale	VL	L	M	H	VH	weight
VL	1	3	5	7	9	0.513
L	1/3	1	3	5	7	0.261
M	1/5	1/3	1	3	5	0.129
H	1/7	1/5	1/3	1	3	0.063
VH	1/9	1/7	1/5	1/3	1	0.034

TABLE 5 : Five-point rating scale(b).

scale	VS	S	M	L	VL	weight
VS	1	3	5	7	9	0.513
S	1/3	1	3	5	7	0.261
M	1/5	1/3	1	3	5	0.129
L	1/7	1/5	1/3	1	3	0.063
VL	1/9	1/7	1/5	1/3	1	0.034

The experiment assumes each Machine ID attribute in table part-00000-of-00500 denotes a VM. 500 VMs are sampled as the experimental dataset. Each VM has 10 items of task usage. Next, we need to map the raw data according to the proposed rating scale. For single value, mean, maximum and minimum value is first to be calculated based on all the 500 VMs raw data. Then, the raw value of such attribute is mapped into partitions according to five-point rating scale. According to AHP model of task evaluation, every VM is evaluated and the proper representative task usage data is obtained. Table 6 show us the task evaluation of one VM with only two task data for example. Table 7 show us 5 tasks with highest value after applied the model. Then we are able to load task usage data into VM migration evaluation model respect to Table 7. Table 8 shows the VM evaluation of VM with only two VMs as the example.

Obviously, after all tested VM machine been applied with the proposed model, the VM with the highest value should be migrated first. Table 7 tells us the result. And VM with VM_ID 33 has the highest value. It shall be first put into ACVMM. Next, we need to find other VMs which have higher similarity with VM_ID 33.

TABLE 6 : Task usage evaluation.

C	SC	GW	Task 1		Task 2	
			Score	GW	Score	GW
B1	B_{11}	0.311	0.51	0.160	0.51	0.160
	B_{12}	0.052	0.26	0.014	0.51	0.026
B2	B_{21}	0.057	0.51	0.029	0.03	0.002
	B_{22}	0.010	0.51	0.005	0.51	0.005
B3		0.570	0.03	0.019	0.06	0.359

TABLE 7 : Task evaluation result.

VM ID	Task ID	value
33	10	0.397493
52	10	0.379425
375	10	0.329093
281	10	0.327542
129	9	0.29349

Vm similarity calculation

Before similarity calculation, same five-rating scale has been applied to each VM for reducing the amount of computation. The mapped data are then transformed according to VM attributes matrix as shown in Table 3. That is to say, to decide whether an attribute of a VM agreed the value over 10 task data. As the migration VM should contain value that has very low CPU rate, very low maximum CPU rate, very short cycles per instruction and very long task duration, VM attributes matrix is able to be obtained based on such definition. For single task usage data, we assign 1 to the data that have certain attribute value, 0 to the rest of the data.

TABLE 8 : VM migration evaluation.

C	SC	GW	VM 1		VM2	
			Score	GW	Score	GW
C1	C11	0.729	0.51	0.160	0.513	0.160
	C12	0.104	0.26	0.014	0.513	0.027
C2	C21	0.139	0.51	0.029	0.034	0.002
	C22	0.028	0.51	0.005	0.513	0.005

TABLE 9 : Similarity result.

VM ID	similarity
47	0.358317
82	0.358264
93	0.358186
292	0.358183
257	0.357986

Experiment dataset is similar with AHP model application. Again five-point rating scale is applied to 500 VMs raw data to formalize VM attributes matrix. Similarity among each of 499 VMs toward VM_ID 33 are calculated. Table 9 illustrates the top 5 VMs with highest similarity after result ranking from similarity calculation according to formula (1), (2) and (3). Next, all VMs are clustered by casting VM clustering algorithm on the similarity values. The cluster granularity can be adjusted by system administrators as application scenario varies. Consequently, the cluster that contains VMs with highest similarities is the ACVMM. Thus ACVMM is a strong reference for system administrators to migrate VMs onto physical machine that always powered on. Finally, switch off the original host machine will reduce the overall energy consumption the cloud server cluster. The proposed method is conducive and practical to environmental protection, it strengthened the concept of green cloud computing.

CONCLUSION

In this paper, we proposed an AHP-based model in order to evaluate migrate VM identification decisions. By conducting an usability study with VM task resource usage data and then demonstrating how the model can be applied in real applications, the paper investigates how easy the proposed AHP model is to work with. Furthermore, an attribute clustering based collaborative filtering method has been applied for identifying migrate VM. The method first introduced a VM attribute space to summarize the node rate score into number of feature clusters. Then based on the AHP result, it calculates similarities between VMs. Both methods are verified with real dataset and thus achieved acceptable result to identify migrate VM. The experiment result shows certain achievement. However, other features of a VM have not included in this paper, then our method is still relatively simple as there are many details need to be further studied. Hopefully, this work will motivate researchers to investigate solution to the identification of migrate VM and preserve the green cloud computing.

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