International Journal of Smart Business and Technology
Vol. 3, No. 1, (2015), pp. 1-14
http://dx.doi.org/10.21742/ijsbt.2015.3.1.01

A Novel Dynamic Virtual Machine Consolidation Algorithm based on Correlation Coefficient Analysis and Bin Packing

Changming Zhao[1] and Jian Liu[2]

[1] *School of Communication and Information Engineering (SCIE), University of Electronic Science and Technology of China (UESTC), Chengdu 611731, China*
[2] *School of Computer and Communication Engineering, University of Science and Technology Beijing (USTB), Beijing 100083, China*
[1]*zcome@126.com*, [2]*liujian@ustb.edu.cn*

Abstract

Virtual Machine Consolidation (VMC) is known as a crucial method to improve system resource utilization and service level agreement in a data center. In this paper, we propose a novel algorithm named Segmentation Iteration Correlation Combination (SICC) expressly for the VMC. In this algorithm, we integrate the methods of statistic regression modeling, Pearson correlation coefficient analysis and off-line Bin packing to establish a new process strategy to achieve excellent higher one dimensional resource utilization of a data center. The SICC operates based on an innovative two-stage strategy: the first stage is to divide all the Virtual Machines (VM) into several groups and reduce the peak-mean difference value of the VM resource utilization inside each VM group as much as possible by the Correlation Coefficient Serial analysis and one kind of improved VM dynamic complementary consolidation algorithm, derived from the algorithm of Iterative Correlation Match Algorithm (ICMA). When the difference of peak-mean value is small enough, we can take advantage of the Bin Packing methods in the second stage to improve resource utilization on account of the reasonable VM consolidation order. The numerical simulation indicates that the algorithm features a 3% to 20% performance improvement in resource utilization to the ICMA algorithm and approximate 50% performance improvement in resource utilization to First Fit Decreasing (FFD) with the same dynamic initial conditions.

Keywords: *Pearson correlation coefficient, First fit decreasing*

1. Introduction

Recently, the requirement for process power of data centers is increasingly urgent. Construction and maintenance a data center usually concerns huge resource consumption. In contrast to that, the servers in data centers are also well known for low average utilization. According to statistics from different sources, the data centers in America consumed approximately 2% electric power, whereas the average utilization of serves was only 10% to 19%. [1] And around the world, the whole data service industry faces the same problem. Therefore, how to dramatically improve the server average utilization is a high value research topic.

The traditional Virtual Machine Consolidation (VMC) algorithms can be classified into two sets, including static algorithms and dynamic algorithms. The static algorithms are named

Article history:
Received (February 7, 2015), Review Result (April 10, 2015), Accepted (May 14, 2015)

Print ISSN: 2288-8969, eISSN: 2207-516X IJSBT

static models and these static models are generally simplified as some kinds of special off-line Bin Packing model. The FFD heuristic algorithms [2] and intelligent programming algorithms [3] are frequently used static algorithm VMC in scholarly works. And the static algorithms usually benefit from the static model as preferable global optimization performance and low calculation cost. This is a type of mature and good performance theory to deal with the VMs with low dynamic characteristics. However, the advantages also encumber the algorithms with extremely poor dynamic resource utilization that, considering the SLA requirement, the VM's utilized capacity must be set as VM's peak resource utilization. It may cause a mass of new resource fragmentation in the static algorithm process.

Contrary to the static VMC algorithm, the dynamic VMC algorithms pertinently aim to better utilize the resource complementation in the time domain and absence of design for resource overall optimization. There are several primitive dynamic strategies for VMC, such as peak allocation placement of One-time Consolidation (OTC), which means each VM has only one chance for consolidation, based on rough tendency estimation for resource utilization [4]. However, these methods are deeply flawed in SLA or resource utilization. Verma proposed an improved OTC algorithm named Placement Based Correlation (PCB) [5]. If two VM's utilization tendency is roughly complementary and the summary of their nominally average utilized capacity is no more than one VM's upper limit of resource reservation, we can regard the two VMs as good multiplexing pair. The algorithm achieves a balance in resource utilization and SLA based probability criterion to some extent. But it is also of low performance in complementariness.

R. Apte and L. Hu propose an improvement of schemes and it can reflect the complementariness strategy more accurately [6]. The type of schemes introduces statistic tools, such as statistic regression analysis and Pearson correlation coefficient formula, to obtain better effect in the calculation of complementary. The type of schemes could achieve a preferably complementary VM multiplex process by more precise value forecasting and correlation analyzing. But it still does not perfect in the VM consolidation that some scholar work indicated some VM consolidated pair is still of consolidation potential once more. Jian Wan and Fei Pan propose a modified edition strategy on account of the above reason, called the Iterate Correlation matching algorithm (ICMA) [7]. This algorithm is the same as the previous one in the mass but still keeps the VM consolidated pair in the queue instead of deletion. The algorithm is of satisfied enough performance in the dynamic consolidation process. However, there is one crucial defect as before that the whole consolidation process is according to the current minimum correlation coefficient completely but ignoring to adjust VM consolidation sequence as an average resource utilized capacity. In terms of off-line Bin packing theory, it may result in an integer programming problem in the VM consolidation process when some high average resource utilized capacity VMs appears in the latter part of the matching sequence.

However, the dynamic algorithms are difficult to coordinate with static algorithms that almost all of current algorithms must be a trade-off between the two strategies. The most difficult to modify the static strategies with dynamic viewpoint is hard to accurately estimate the VM's future resource utilization and complementation, and make good use of these dynamic parameters in a static model without new resource fragmentation phenomenon. We propose a novel scheme for VMC to integrate the two types of quite distinct algorithms. The strategy of the SICC is based on reducing the Peak-Mean value of VM's resource utilization with one improved dynamic algorithm while one preprocessed VMs, called Consolidated Virtual Machine (CVM), is of warrant close Peak-Mean resource utilization. Then, it can avoid dynamic resource waste to the greatest extent when we make use of peak utilization as

VM's utilized resource capacity. The original intention of designing SICC is that the unreasonable consolidation order of dynamic complementary consolidation may influence the final resource utilization of CVMs seriously in theory when the original heavy resource utilized VMs reach a high proportion. And it is owing to the consolidation order of the dynamic consolidation ICMA algorithm completely depending on resource utilization complementary degree. According to the Correlation Coefficient Serial and Bin Packing theories, the serious drawback may result in the kind of high resource utilization VMs, known as large items in the Bin Packing model, occurring at the latter part of the VM consolidation serial randomly. And these oversize items may cause the 0-1 integer programming problem. Despite the drawback, the improved ICMA is still a highly useful algorithm when we change the algorithm optimization object from the current maximum consolidation complementary degree to the minimum average Peak-Mean difference. Once the average Peak-Mean difference is shrunk to the minimum, we can use the mean resource utilization instead of peak resource utilization and make use of FFD, which is a static Bin Packing algorithm of preferable global optimization, in theory, to complete the remaining consolidation process. Then the SICC can also achieve the overall gain similar with static algorithms much better than pure dynamic algorithms.

2. System models

The basic VMC algorithms mechanic can be simplified as a two stages Bin Packing process that the primary stage combines all the task requests to dedicated VMs to ensure map all the task requests with minimization VM numbers and the second stage also map the packed VMs queue to minimization servers. In this paper, we simplify all the VM are of the same only one dimensional resource reservation capacity, called standard capacity VM. On the assumption, the complexity of the secondary stage map can be reduced to the limit and it can be more beneficial for us to analyze the SICC algorithm's principle and efficiency.

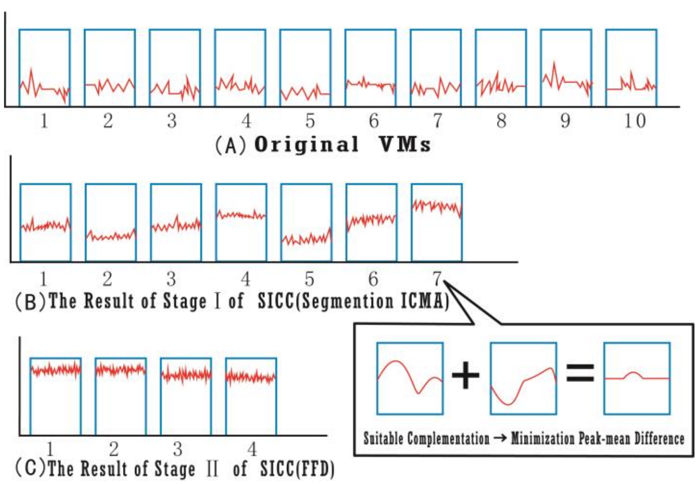

Figure 1. The main process of SICC algorithm

The proposed SICC's strategy integrates the advantages of the two types of traditional strategies. The scheme is drawn in Fig.1.Our novel algorithm makes a two-stage process. In the first stage, we segment the original VMs into three parts, named large, medium and small size VM. They respectively correspond to VM resource utilization of less than 25%, between 25% and 50% and more than 50%. Then it preprocesses these original VMs with ICMA separately with the condition of correlation coefficient less than negative 0.5 in every size segment and makes use of the separately preprocess CVMs to run ICMA in the global scope again. The mechanic of the Iterate Correlation matching algorithm (ICMA) is the best off-line dynamic consolidation strategy in current. The algorithm ensures the VM in Fig.1A always consolidates with the best complementation VM, known as the VMs pair corresponding to the lowest negative correlation coefficient, in the store queue. Then it needs to send the CVM back to the store queue again and iterates the process until there is no VMs pair corresponding to the negative correlation coefficient in the store queue. In Fig.1B, when the consolidation process is highly complementary, the new consolidated VM (CVM) is of comparative little difference between peak and mean utilization. CVM must reconsolidate by high global gain static algorithm FFD in Fig.1C. In the second stage, we run the preprocessed CVMs with FFD to achieve global consolidation gain. Therefore, the overall consolidation gain of SICC consists of two parts of stage gains of static gain and dynamic gain.

And we make a point that running improved ICMA segmentary and partially with some restrictive conditions may lead to the resource utilization distribution of CVM closer to uniform distribution while the average mean value and Peak-Mean difference of CVM are still fairly low and the number of CVM is minimized. Mark Allen Weiss indicates that if we can combine all the original items to a new items group as uniform distribution, it may ensure the approximation minimization amount of bins with FFD algorithm [8]. We provide all the specific formulation analyses in Part 3.

3. Proposed SICC algorithm

As the description in Part 2, the first stage of SICC is a segmentary improved ICMA. The improved algorithm includes Auto-Regressive and Moving Average Model (ARMA) time serial analysis, Pearson linear correlation coefficient analysis. And the second stage of the SICC performs an FFD algorithm. In the progress, the ARMA analysis is used for forecasting the resource utilization of VM and Pearson linear correlation coefficient analysis is severed as the tool for searching the best complementary VM pairs. In this part, we formulate all the stages of the algorithm and give a corresponding effect analysis.

3.1. ARMA model and pearson correlation coefficient

If the sample values of a random time series $\{x_t\}$ of stationary, normality and zero-mean are correlative with not only the forward n steps value $x_{t-1}, x_{t-2}, \cdots, x_{t-n}$ and also forward m steps interference $a_{t-1}, a_{t-2}, \cdots, a_{t-m}$. According to multiple linear regression theory, we can obtain the general ARMA model:

$$X_t = \sum_{i=1}^{n} \phi_i x_{t-i} - \sum_{j=1}^{n} \theta_j a_{t-j} + a_t \qquad a_t \in N(0, \sigma_n^2) \tag{1}$$

Based on equation (1), we can establish one type of short-range dependence forecast for the resource utilization in a period time future. In this paper, we adopt 1440 sampling points totally to stand for one day time series.

When we estimate the time series of all the original VMs, we can search for the current best complementary VMs pair. We set the $\{x_t^1\}$ and $\{x_t^2\}$ stands for the resource utilization of two VMs in the future with the ARMA model. Then the Pearson linear correlation coefficient can be defined as follows:

$$r = \frac{\sum_{t=1}^{1440}(X_t^1 - \bar{X}^1)(X_t^2 - \bar{X}^2)}{\sqrt{\sum_{t=1}^{1440}(X_t^1 - \bar{X}^1)^2}\sqrt{\sum_{t=1}^{1440}(X_t^2 - \bar{X}^2)^2}} \tag{2}$$

In equation (2), the coefficient r is a baseline to measure the correlation of two VMs. The value of coefficient r is of fluctuation between negative 1 to positive 1. When the value equals negative 1, it stands for the two VM's complete negative correlation. And when the value equals positive 1, it stands for the two VM's complete positive correlation. A complementary VM pair corresponds to a negative r value. In particular, we define consolidation which its an r-value less than negative 0.5 as a high complementary consolidation. The relative concept is used in follow SICC analysis.

3.2. Proposed SICC algorithm

In the section, we discuss the SICC algorithm based on two aspects, including the correlation coefficient serial analysis and VM Peak-Mean difference value analysis. According to the two characteristics, we illustrate the theory fundamentals for SICC algorithm design.

3.2.1. The correlation coefficient serial analysis

First of all, we introduce the concept of Correlation Coefficient Serial (CCS) in the algorithm efficiency analysis. The CCS assembles all the correlation coefficients of VM consolidation as their time series in an entire algorithm process. Basically, in some regression statistics research works, the correlation coefficient of two sample sequences can be used to reflect the complementary degree of the two sample sequences. Therefore, the CCS can illustrate the both global and local characteristics of the correlation coefficient serial. The [Figure 2] describes a typical CCS based on the One-Time Consolidation (OTC) algorithm.

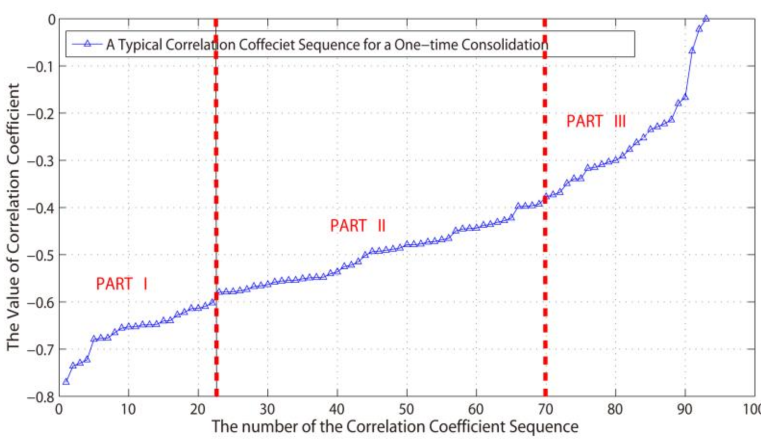

Figure 2. A typical CCS based on an OTC algorithm

As shown in [Figure 2], the typical correlation coefficient serial is a monotone increasing function about the consolidation time series. It is because the correlation consolidation algorithms always select the VMs pair, which possesses the current global minimal correlation coefficient, for consolidating. In the figure, the correlation coefficient serial can be divided into three parts. Part I has a low correlation coefficient value and sharp acceleration value. Part II includes the correlation coefficient samples with medium correlation coefficient value and gentle acceleration. Furthermore, the samples in Part III are of both correlation coefficient values and high acceleration values. One good improved algorithm should increase the consolidation chances in Part I and Part II area as much as possible.

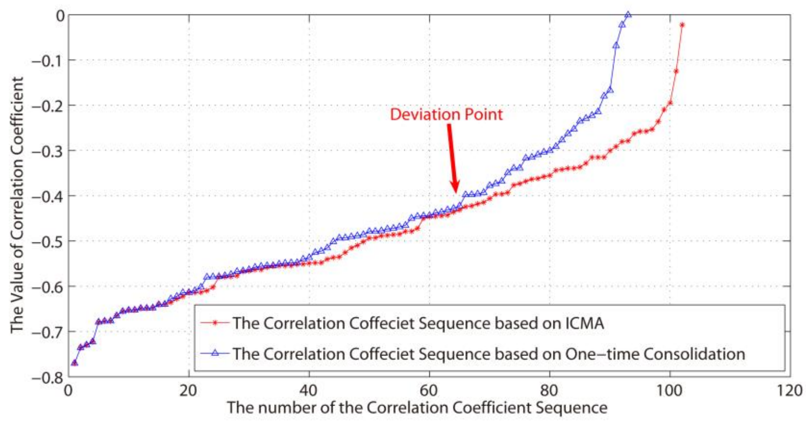

Figure 3. The CSS control group between ICMA and OTC

[Figure 3] provides an algorithm efficiency control group between ICMA and OTC algorithms with CCS. It is shown that ICMA is true of longer CCS than OTC. However, the increment samples of CCS by ICMA are mainly distributing in Part III that the number of sample points in ICMA is nearly the same as the OTC in Part I and Part II. And the values of corresponding samples in ICMA and OTC are no evident difference till the deviation point appearing at the end of Part II. Therefore, the schedule of ICMA is still not a perfect algorithm improvement method that all the new increment consolidation chances belong to low complementation consolidation.

To achieve higher consolidation gain than OTC and ICMA, the first method we proposed is VM randomized grouping. The randomization method divides all the raw VMs into several groups. Therefore, it may be impossible to achieve a global minimization correlation coefficient inside any one VM group. But we can obtain more suboptimal results in every group. Hence, the output CCS can keep more samples in Part I and Part II than ICMA and OTC which belongs to the conventional scheduling and consolidation process. We utilize the concept as one important component in our proposed algorithm SICC.

3.2.2. The peak-mean difference value snalysis

We introduce Peak Utilization Bar (PUB) to measure the algorithm efficiency. The CCS includes the correlation coefficient to each consolidation incomplete algorithm progress and PUB illustrates the nominal resource utilization of each VM of the actual algorithm result.

The primary problem is defining the Peak Resource Utilization (PRU) model of CVM and researching the way to measure the influence, which is caused by correlation coefficient value, to PRU.

International Journal of Smart Business and Technology
Vol. 3, No. 1, (2015), pp. 1-14

We assume the PRU of the ith VM is P_i, and the vector serial of resource utilization of the ith VM is $\vec{S}_i$, in which limits $i \in [1,2]$. Then, the PRU of the CVM is expressed as:

$$\begin{aligned} &P_{CVM} = \max(\overrightarrow{S_1} + \overrightarrow{S_2}) \\ &s.t. mean(\overrightarrow{S_1}) + mean(\overrightarrow{S_2}) \le P_{CVM} \le \max(\overrightarrow{S_1}) + \max(\overrightarrow{S_2}) \end{aligned} \tag{3}$$

Because the serial $\vec{S}_i$ is a vector stochastic process, it is no possible to estimate the peak point $\vec{S}_{CVM}$ without calculation the summary of the serials of $\vec{S}_1$ and $\vec{S}_2$. The PRU of P_{CVM} may be influenced by the values and positions of PRU points of the two original VMs more than the complementary degree of two original VMs.

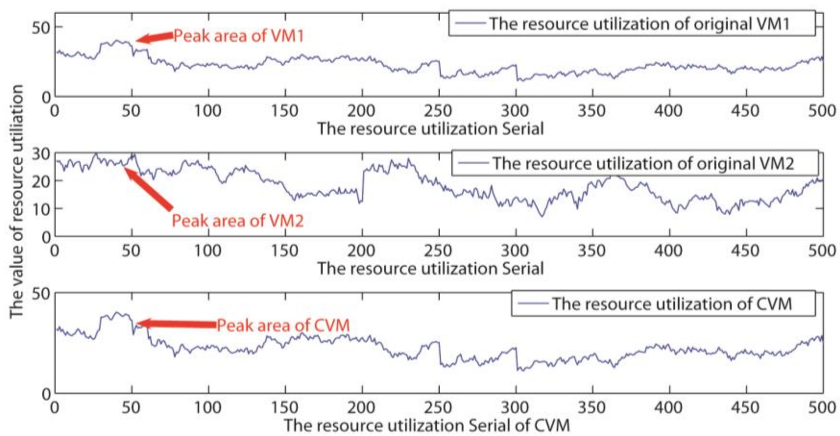

Figure 4. The PRU analysis of a case of '-0.42'correlation coefficient

For example, [Figure 4] is a sketch to show a simple case about the uncertainty between the correlation coefficient of VMs and the PRU of CVM. In the figure, the correlation coefficient is only '-0.42'. We can estimate the coefficient value by the relatively high complementation degree. But the CVM from the two VMs still has a positive correlation and high value PRU. Therefore, we cannot simply assert the correlation between the low correlation coefficient and low PRU.

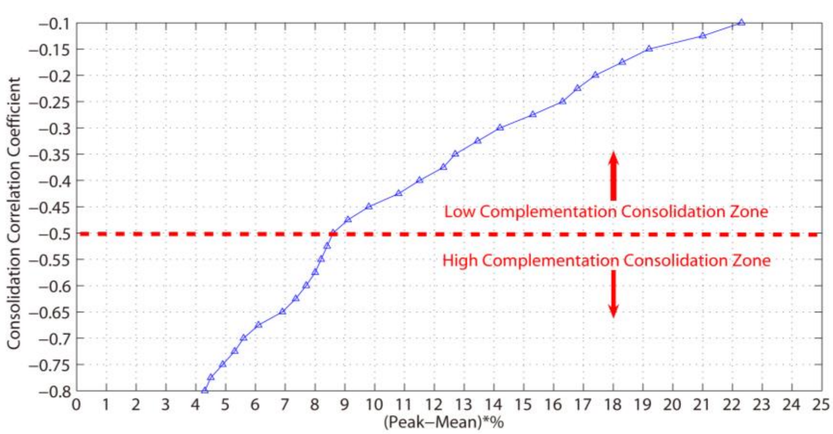

Figure 5. The average PMD at different correlation

However, other research results indicate there is also some connection between these two parameters. We analyze more than one hundred thousands of negative correlation coefficient instances in thousands of simulation experiments to get the regression statistics to result that the corresponding difference between PRU and mean resource utilization of CVM can contain in a relatively small and linear when the correlation coefficient is less than $N_{0.5}$

The data in Fig.5 indicate if the correlation coefficient is less than negative 0.5, the difference of Peak mean difference (PMD) is less than 8.63% typical reservation resource. Then, we can get the rule as follow: When the correlation coefficient of one pair of VMs is less than negative 0.5, there is a value of PRU satisfying:

$$\begin{aligned} &P_{CVM} \approx mean(\overrightarrow{S_1} + \overrightarrow{S_2}) \\ &s.t. \text{CorrelationCoefficient} \leq -0.5 \end{aligned} \tag{4}$$

In other words, if the correlation coefficient (CC) of one VMs pair is less than negative 0.5, we can make use of the mean value of CVM instead of PRU without fear of resource wasting. This is the second method to improve algorithm efficiency.

On the other hand, another crucial problem of this section is to research and improve the VM consolidation order in ICMA. Most of our research results point to the drawback of low resource utilization on unreasonable VMs consolidation orders. We assume SICC has a two-stage VMs consolidation process. All the VMs reduce the dynamic characteristics in the first stage by a type of improved ICMA. And the ideal algorithm can ensure that the newly generated VM-CVM group is suitable for the traditional static FFD process.

We assume $S = (s_1, s_2, ...s_n)$ is the current original VMs group. And the sequence $B = (b_1, b_2, ...b_m)$ is the current CVMs and VM mix serials. We set $DistU(B)$ to stand for the ratio of the utilization upon 50% CVMs to the amount of group mixed CVMs and VMs and $DistR(b_1, b_2)$ to stand for the correlation coefficient of pair (b_1, b_2) .

In Stage I of SICC，we can integrate use the method mentioned in Chapter 3.2.1 and equation-(4) to reduce the Peak-Mean value of remaining CVMs. In the process of Stage I, we should prohibit the original VMs of utilization less than 25% dynamic consolidating with each other to be the CVM of utilization between 40% to 50%, it also prohibits the pair (b_1, b_2) of $DistR(b_1, b_2)$ more than negative 0.5 consolidating. The theorem can effectively avoid the CVMs of over-high utilization consolidated too much and save the VMs of utilization below 25% for stage II as much as possible. Based above conditions, in stage II, we can make good use of FFD to achieve more order gain [9].

In Stage II of SICC, it can achieve the minimization number of CVMs when the original distribution of CVMs resource utilization matches uniform distribution. According to Bin Packing theory, the Bin Packing algorithm can get the best average behavior when the capacities of items form with a uniform distribution. In theory, if there are N items with pure uniform distribution, the best packing result is N/2 [10].

To solve the problems mentioned above, we develop the improved algorithm SICC, which is executed, based $ICMA_{-0.5}$ and the FFD algorithm. In these algorithms, we use 'CC' to denote the correlation coefficient and '$Coeff_{\min}$' to express the minimization correlation coefficient in the correlation coefficient matrix. Finally, the term 'resource utilization' is abbreviated to 'RU'.

The algorithm $ICMA_{-0.5}$ is denoted as **Algorithm1** and the algorithm SICC is denoted as **Algorithm2**.

Algorithm1 $ICMA_{-0.5}$

---

1 *Make all the current N VMs/CVMs in the store group for consolidation.*

2 *Make a $N \times 1440$ raw sample data matrix as the equation $-(1)$ and a $N \times N$ CC matrix correspoinding to the store group as the equation $-(2)$.*

3 *Find the $Coeff_{\min}$ in the matrix.*

If $Coeff_{\min} \le -0.5$ & $\mathrm{PRU}_{CVM} \le 100\%$

- Set $N = N - 1$;
- Record the current $Coeff_{\min}$;
- Replace the two VMs with the new CVMs in the $(N-1) \times 1440$ raw sample data matrix and $(N-1) \times (N-1)$ CC matrix ;

else if $Coeff_{\min} \le -0.5$ & $\mathrm{PRU}_{CVM} > 100\%$

- Set $Coeff_{\min}$ =1 and Return to Step 3

else if $Coeff_{\min} > -0.5$

- Algorithm end

Algorithm2 SICC

---

1 Divide all the original VMs into 3 sections,

If $RU < 25\%$

- make VMs in section1,and run $\mathrm{ICMA}_{-0.5}$ in section1;

else if $25\% < RU < 50\%$

- make VMs in section2,and run $\mathrm{ICMA}_{-0.5}$ in section2 ;

else if $RU > 50\%$

- make VMs in section3,and run $\mathrm{ICMA}_{-0.5}$ in section3 ;

2 Combine all the rest VMs/CVMs together from the Step 1 and run $\mathrm{ICMA}_{-0.5}$ again.

3 Calculate each $\mathrm{PRU}_{\mathrm{CVM}}$ of the raw sample data matirx from Step 2, and store $\mathrm{PRU}_{\mathrm{CVM}}$ sequence in a list.

4 Descending sort the $\mathrm{PRU}_{\mathrm{CVM}}$ list and run FFD algorithm with the descending list.

---

4. Simulation results

In the Section, we provide extensive simulations to evaluate the performance of the proposed SICC algorithm and then compare it with that of the ICMA instance. Throughout these simulation studies, we assume the system includes 195 original VMs of real resource utilization and the primary system runs with the SICC algorithm and the secondary system runs with the ICMA. The peak resource utilization of 195 original VMs distributes as the condition that means equaling to 30% standard VM capacity and standard equaling to deviation 15% standard VM capacity [11][12]. In these original VMs, there are 17 small VMs, 136 medium VMs and 42 large VMs, corresponding to less than 25%, between 25% with 50% and more than 50% respectively.

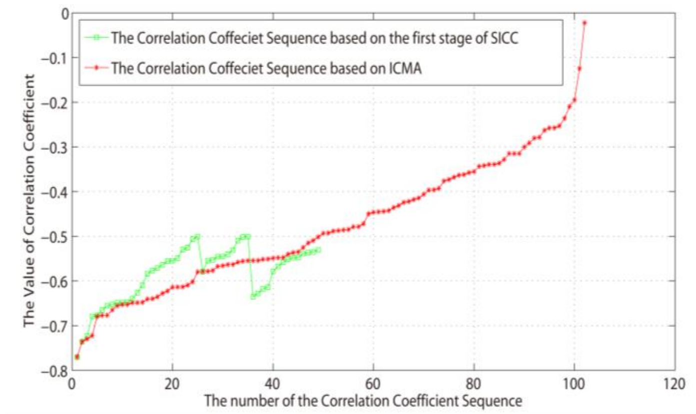

Figure 6. The CSS control group between the first stage of SICC and ICMA

First, as our description in the above chapter, the CCS of SICC has more correlation coefficient samples in Part I and Part II area of Fig.6. Hence, Fig.6 proves that the SICC algorithm can make use of the relative higher correlation coefficient of each VM pair to exchange more consolidation chances in Part I and Part II. The characters can ensure the SICC algorithm achieves a lower average correlation coefficient value in its first stage than ICMA and OTC. Meanwhile, the SICC can also permit VMs to consolidate another VM with a low correlation coefficient in the latter part of CSS. As regards the VMs with high mean resource utilization and low consolidation potential, the characteristic can cause enormous efficiency impact in the consolidation process.

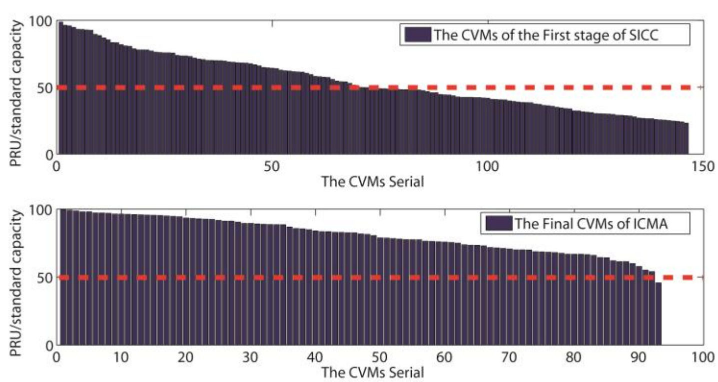

Figure 7. The CVM number contrast between stage I of SICC and ICMA

Second, [Figure 7] draws the utilized capacity contrast between ICMA and ideal algorithm SICC in Stage I. Compare with the No.1 and No.2 figure in [Figure 7], it is obvious that the ICMA is of fewer rest CVMs but also less reconsolidation potential. It is because almost all of the rest CVMs are over the threshold of 50 % reservation capacity of one standard CVM. In other words, excessive consolidation maybe not a good selection in stage I when it may result in a CVM with too high resource utilization. Therefore, in stage I, we should monitor the consolidation process in case overmuch small VM, known as less than 25% of standard resource reservation, are sent to consolidate with each other under the low complementary conditions.

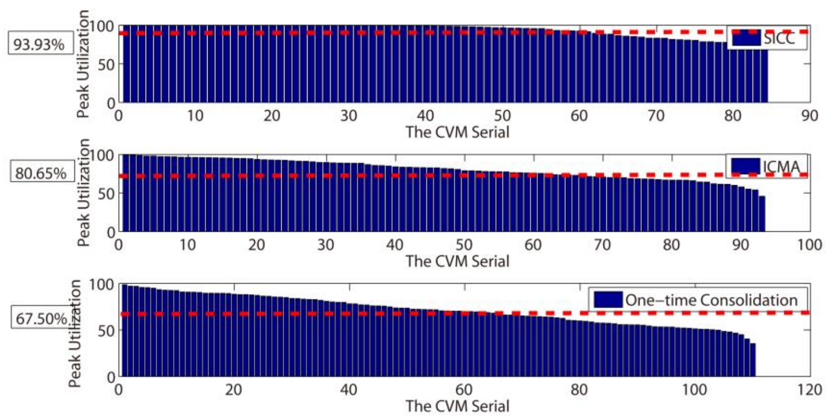

Figure 8. The final CVM number contrast between SICC, ICMA and OTC

Finally, we depict the rest CVMs between ICMA and SICC after the second stage of the algorithm as the same initial conditions of Fig.8. The result shows the final rest CVMs of SICC are less than the rest CVMs of ICMA and OTC. The average peak resource utilization of SICC is less than the parameter of ICMA by 13% and the parameter of OTN by 24%. It also dedicates that this algorithm is adept at VMs consolidation efficiency and reasonable consolidation order.

5. Conclusion

In this paper, we study the problem of VM consolidating in peak resource utilization under time-variant conditions. First of all, it is the unreason consolidation order that we focus on the dynamic consolidation algorithm of ICMA and indicate the main drawback to decrease performance improvement of ICMA. Besides, we also formulate an unreason consolidation order problem with Correlation Coefficient Serial analysis and Peak-Mean difference value analysis. We propose a novel VM consolidation algorithm, called SICC, to integrate the advantages of the dynamic and static consolidation algorithms based on reducing the Peak-Mean difference value of the VM and the order gain of the FFD algorithm. Finally, the results show that the proposed algorithm can sharply increase the probability of high complementation consolidation and reduce the Peak-Mean difference value of consolidation VMs pair in the given conditions. Both the works improve the algorithm efficiency for resource utilization significantly. In future work, we will investigate the proposed algorithm in a two-dimensional resource reservation process.

Acknowledgment

This work is supported by the National Major Projects (No. 2015ZX03001013-002), the National Natural Science Foundation of China (No. 61173149), the Fundamental Research Funds for the Central Universities, and the Beijing Higher Education Young Elite Teacher Project.

References

[1] C. Papagianni, A. Leivadeas and S. Papavassiliou, "On the Optimal Allocation of Virtual Resources in Cloud Computing Networks", IEEE Transactions on Computers, vol.62, no.6, **(2013)**

[2] A. Beloglazov, J. Abawajy and R. Buyya, "Energy-aware Resource Allocation Heuristics for Efficient Management of Data Centers for Cloud Computing", Future Generation Computer Systems, vol. 28, no. 5, May, pp. 755-768, **(2012)**

[3] R. Buyya, R. Ranjan and R.N. Calheiros, "Intercloud: Utility-Oriented Federation of Cloud Computing Environments for Scaling of Application Services", Algorithms and Architectures for Parallel Processing, Computer Science, vol.608, pp. 13-31, **(2010)**

[4] X. Meng, C. Isci, J. Kephart, L. Zhang, E. Bouillet and D. Pendarakis, "Efficient Resource Provisioning in Compute Clouds Via VM Multiplexing[C]", The 7th International Conference on Autonomic Computing (ICAC), New York, USA, pp.11-20, **(2010)**

[5] A. Verma, G. Dasgupta, T. K. Nayak, D. Pradita and R. Kothari, "Server Workload Analysis for Power Minimization Using Consolidation", USENIX Annual Technical Conference, **(2009)**

[6] R. Apte, L. Hu, K. Schwan and A. Ghosh, "Discovering Dependencies between Virtual Machines Using CPU Utilization[C]", USWNIX The 2nd Conference on Hot Topics in Cloud Computing (HotCloud), Berkeley, California, USA, pp.17-23, **(2010)**

[7] J. Wan, C.F. Jiang, X.H. Xu and F. Pan, "Placement Strategy of Virtual Machines Based on Workload Characteristics", IEEE 26th International Parallel and Distributed Processing Symposium Workshops and PhD Forum (IPDPSW), **(2012)**

[8] M.A. Weiss, "Data Structures and Algorithm Analysis in C", Second Edition, Pearson Education Inc., Chapter 10. 1. 3 Approximation Algorithms for Bin Packing

[9] J.L. Bentley and D.S. Johnson, "Some Unexpected Expected Behavior Results for Bin Packing", STOC'84 Proceedings of the Sixteenth Annual ACM Symposium on Theory of Computing, pp. 279-288.

[10] P.A. Dinda, "The statistical properties of host load", Fourth Workshop on Languages, Compilers, and Run-Time Systems for Scalable Computers, pp. 1-23.

[11] S. Martello and P. Toth, "Knapsack problems: Algorithms and Computer Implementations", Wiley

[12] A. Mishra, J.L. Hellerstein and W. Cirne, "Towards characterizing cloud backend workloads: Insights from google compute clusters", ACM Sigmetrics Performance Evaluation Review, vol.37, no. 4, pp.34-41, **(2009)**

Authors

Changming Zhao received his B.S. degree in Sichuan University, China, in 2007, the Msc degree in Communication Engineering from The University of Manchester, UK, in 2009. He is currently a PHD candidate in the School of Communication and Information Engineering from University of Electronic Science and Technology of China. His research interests include resource virtualization, C-RAN and Next Generation Networks.

Jian Liu received his B.S. degree in Automatic Control Theory and Applications from Shandong University, China, in 2000, and the Ph.D. degree in School of Information Science and Engineering from Shandong University in 2008. He is currently an associate professor of University of Science and Technology (USTB), Beijing, China. His research interests include cognitive radio networks, mobile mesh networks, and LTE-A.

This page is empty by intention