Available online at www.sciencedirect.com
ScienceDirect
Procedia Computer Science 87 (2016) 122 – 127
Procedia Computer Science

2016 International Conference on Computational Science

Prediction Model for Virtual Machine Power Consumption in Cloud Environments

T. Veni*, S. Mary Saira Bhanu

Department of Computer Science & Engineering, National Institute of Technology, Tiruchirappalli 620015, Tamil Nadu, India

Abstract

Power consumption has become a crucial issue in cloud computing environments because of environmental and financial concerns. It is necessary to estimate individual virtual machine power consumption to enforce efficient power aware policies in cloud. Existing solutions are built on linear power models to infer power consumption through VM resource utilization. However, linear models do not capture dependencies among multiple parameters and hence they do not ensure prediction accuracy across multiple workloads. In this paper, a non-linear support vector regression based power model using performance monitor counters is proposed to predict individual virtual machine power consumption. Experimental results with various standard benchmark workloads demonstrate that the prediction accuracy of proposed approach is better than the existing linear regression based power model.

Peer-review under responsibility of the Organizing Committee of ICRTCSE 2016

Keywords: Cloud Computing; Virtual Machine; Power Consumption; Power Prediction Model; Performance Monitor Counter.

1. Introduction

Cloud computing is an important computing paradigm which facilitates dynamic flexible provisioning of services over the internet[1]. In cloud environment, power consumption has become a critical issue because of an operational expenditure as well as environmental impact due to CO_2 emissions. It is evident from existing literature that operational expenditures for powering and cooling of cloud data center resources will soon exceed the acquisition cost[2]. Hence, it is essential to enforce power aware solutions in cloud computing environment.

Most of the existing power aware solutions employ external hardware power meter to estimate the power consumption of whole server. However, measuring individual virtual machine (VM) power consumption is inevitable for implementing efficient power aware resource provisioning and pricing techniques in cloud environment. Moreover, it is very difficult to estimate individual VM power consumption in a shared virtualized environment.

*Corresponding author.
E-mail address: venithangaraj@gmail.com

Peer-review under responsibility of the Organizing Committee of ICRTCSE 2016
doi:10.1016/j.procs.2016.05.137

In existing literature, the linear models are used to deduce individual VM power consumption via VM resource utilization or hardware Performance Monitor Counters(PMC)[3,4,5,6,7,8]. However, the metrics used in the power models are correlated with each other. For example, the metrics of CPU utilization may be highly correlated with the metrics of memory utilization, since overwhelming of memory usage would lead to more CPU resource usage. The existing linear models do not capture the dependencies among the metrics which not only decreases the accuracy but also increases the complexity of power prediction.

In order to mitigate this issue, in this paper, a non-linear based Support Vector Regression (SVR) model using hardware PMC is proposed for accurate estimation of VM power consumption. SVR is used to model complex higher dimensional real-world problems with limited training samples. The hardware PMC events are used to accurately capture the VM resource utilization across multiple heterogeneous platforms. Experimental results with various benchmark workloads demonstrate that the proposed power model improves the accuracy of prediction than the existing linear regression based power model.

The rest of this paper is organized as follows. Section 2 reviews the related work regarding VM power model. Section 3 presents the details of the proposed power model. Section 4 illustrates the experimental results and finally, Section 5 concludes the paper.

2. Related Work

Modeling power consumption in virtualized environments is an active research topic. Many research works addressed the issue of per-VM power modeling. Kansal et al.[3] proposed a joulemeter VM power metering approach without guest OS modification. CPU, memory and disk components were considered for modeling power consumption. This approach was extended to provisioning process in virtualized environments. Krishnan et al.[4] proposed a VM power consumption model using two hardware PMC events such as instruction retired (inst_ret/sec) and LLC (Last Level Cache) misses for modeling power consumption of CPU, and memory. Cherkasova et al.[5] proved that I/O virtualization process consumes more power because of its CPU resource demand.

Bohra et al.[6] proposed four dimensional linear weighted regression based power model by correlating the power consumption of different components such as CPU, memory, cache, and disk. Bircher et al.[7] used hardware PMC events for modeling both server and desktop machines power consumption. Their experimental results demonstrated that selecting suitable hardware PMC events are crucial for building power models.

Bertran et al.[8,9] presented experimental study on investigating the effectiveness and accuracy of PMC based power models in both virtualized and non-virtualized environments. Jiang et al.[10] proposed a Look-Up Table (LUT) method to estimate the power consumption for different CPU and memory states. Though LUT method is flexible and easy to implement, it requires large memory to store LUT for each VM. Roberto et al.[11] provided the empirical investigation for power consumption of virtualization technologies. Chonglin et al.[12] employed a decision tree approach for modeling VM power consumption.

Most of the above works used linear models to estimate power consumption. However, the linear models do not capture the dependency among model parameters which results in inaccuracy of power prediction. Hence, the proposed approach employed non-linear SVR regression model for power prediction, thereby accurately capturing the effects of power consumption via hardware PMC events.

3. Proposed System Model

This section details the proposed system architecture for estimating an individual VM power consumption. The proposed model runs on top of Xen virtualized environment and it is based on black box method which collects modeling information from each VM without guest OS modification. The overall architecture of the proposed system is illustrated in Figure 1 and its major components are described as follows:-

- **Profiler**: -This module periodically profiles hardware PMC events of each VM for every sampling period. The hardware PMC events facilitate monitoring resource usage of each sub components (CPU, RAM, Cache, and Disk) which are highly correlated with total system power consumption. When a physical server is powered on, the PMC events will gather all system-level events which are triggered by various components. In

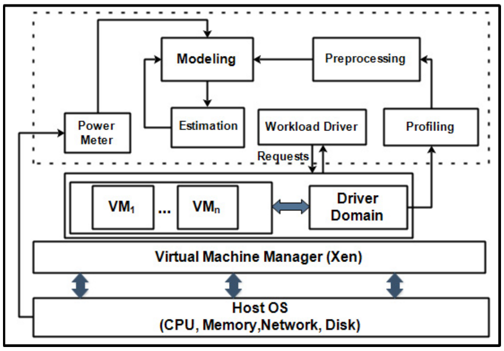

Figure 1. The Proposed System Architecture

order to access the relevant PMC events for each sub components, a system-wide linux profiler oprofile[13] is used for measuring hardware PMC events such as CPU_CLK_UNHAULTED, DRAM_ACCESS, INSTRUCTION_CACHE_FETCHES, LLC_MISS of each process (VM) in standard linux kernel. The iostat tool[14] is used in proposed system to monitor disk usage statistics. In addition, the power meter is externally attached to physical server to measure the actual power consumption. These statistics are sent to preprocessing daemon for further actions.

- **Preprocessing**:- This module parses the log files and sends the resultant information to the modeling daemon.
- **Modeling**: - This module is specifically responsible for capturing relationship between various hardware PMC events with the total power consumption. The pattern of resource features with power consumption varies for different applications and it is not always rigor in linear relationship. Hence, non-linear SVR based power prediction model is proposed to precisely capture the complex relationship between PMC events and power consumption. SVR is a statistical machine learning technique which is used to solve prediction and regression problems. It is based on computing a linear regression in a higher-dimensional feature space where the input data are mapped through a non-linear function. This unique characteristic facilitates SVR to form a non-linear function and extrapolate with limited number of training samples. Typically, SVR uses a ε -intensive loss function. This type of loss function allows from the true target deviation by at most ε. The ε-SVR algorithm does not recognize errors as long as they fall with in $\pm\varepsilon$ boundary of the learned function. Let the terms b and w denote constant and weight coefficients respectively and the term f(t) denotes predicted value which should loosely fit the training data for avoiding over-fitting problems. The SVR algorithm achieves this by making the function to be as flat as possible and the complete problem can be formulated as a convex optimization problem which is shown in equation (1).

$$\text{minimize} \quad \frac{1}{2}\,||w||^2 \qquad \text{Subject to} \begin{cases} f(t_k) - y_k \leq \varepsilon \\ y_k - f(t_k) \leq \varepsilon \end{cases} \tag{1}$$

This convex optimization problem assumes that for every data pair (t_k, y_k) , a function approximates within acceptable ε accuracy. In order to deal with the out of $\pm\ \varepsilon$ boundary errors, the slack variables ξ and ξ^* are introduced which estimate the error for under estimation and over estimation of the actual values. The equation (1) can be rewritten with the addition of two slack variables as

$$\text{minimize} \quad \frac{1}{2}\,||w||^2 + C\sum_{k=1}^{N}(\xi_k^* + \xi_k) \qquad \text{Subject to} \begin{cases} y_k - w^T\phi(t_k) - b \ \leq \ \varepsilon + \xi_k \\ w^T\phi(t_k) + b - y_k \ \leq \ \varepsilon + \xi_k^* \\ \xi_k^*, \xi_k \geq 0 \end{cases} \tag{2}$$

The estimation accuracy of SVR depends on three hyper parameters such as ε , C, and the kernel parameters. The ε parameter sets the accuracy requirement for the optimization function. C determines the penalty associated with constraint violation and it is used to control the trade-off between model complexity and the training error. The kernel parameters can be manipulated depending on the type of kernel. By using lagrange dualization, the above optimization problem can be transformed as

$$f(x) = \sum_{k=1}^{N} (\beta_k^* - \beta_k)\ K(t_k, t_l) + b, \tag{3}$$

where $\beta_k^*\ \beta_k$ are lagrange multipliers and K(t_i, t_j) is called the kernel function. In this paper, the Radial Basis Function (RBF) is used which is shown in equation (4)

$$K(t_k, t_l) = \ exp\ (-0.5\ \|t_k - t_l\|^2\ /\sigma^2) \tag{4}$$

- **Estimation**:- This module is responsible for calculating the system wide power consumption by measuring individual VM power consumption. The individual VM power consumption can be estimated as per the equation (5).

$$P_{dynamic(VM_i)}\ =\ P_{CPU(i)} +\ P_{cache(i)} +\ P_{DRAM(i)} +\ P_{Disk(i)} \tag{5}$$

where $P_{dynamic(VM)}$ is the dynamic power of each active VM. P_{cpu}, P_{cache}, P_{DRAM} are the hardware PMC values of particular VM domain. P_{Disk} is the amount of data transferred for a particular domain. The system wide power consumption can be calculated as shown in equation (6).

$$P_{Total}\ =\ P_{Static}\ +\ \sum_{i=1}^{n} P_{dynamic(VM_i)} \tag{6}$$

where P_{Total} is the total system power consumption and P_{Static} is the static power. This estimation module is also responsible for updating proposed power model when errors exceed a certain threshold.

4. 4. Experimental Evaluation

This section presents the details of experimental testbed, workloads used, and evaluation results in order to demonstrate the accuracy of the proposed power model in comparison with the existing linear power model under diverse workload scenarios.

4.1. Experimental Testbed:

All the experiments were conducted on physical machines (PMs) equipped with 2 quad-core Xeon E5507 processors with 8GB of memory. The physical machines were interconnected with a Gigabit Ethernet. The Ubuntu 12.04 linux distribution and linux kernel v3.2.52 were used on both PMs and VMs. The Xen v4.4.2 was chosen as a virtualization platform. The profiling tool oprofile-0.9.3 with the xenoprofile release version as 0.9.3 was used to profile various PMC events [15]. The system power was measured using WattsUp Pro power meter [16]. The ksvm package in R was used and the default predictor was configured using the following parameters: ε =1.10^{-4}, C=7,σ =2.10^{-2}. The sampling interval was chosen as 2 seconds [6].

4.2. Workloads Used

The different benchmark workloads have been chosen to cover diverse resource usage patterns which are shown in Table 1.

4.3. Experimental Results:

In this section, the accuracy of the proposed approach is evaluated under various workload scenarios. The Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) are calculated as per the equation (7) and (8)

Table 1. Workloads used for Evaluation

Workloads	Description	CPU Intensive?	I/O Intensive?
NAS NBP[17]	NASA benchmark suite for parallel computing evaluation	Yes	
BT	Block tridiagonal	Yes	
CG	Conjugate gradient	Yes	
EP	Embarrassingly parallel	Yes	
IS	Integer Sort	Yes	
LU	Lower-upper symmetric Gauss-Seidal	Yes	
SP	Scalar pentadiagonal	Yes	
MG	Multi Grid	Yes	
Bonnie++ (B++)[18]	Tool for testing file system and disk I/O performance		Yes
GCC[19]	GNU Compiler	Yes	Yes

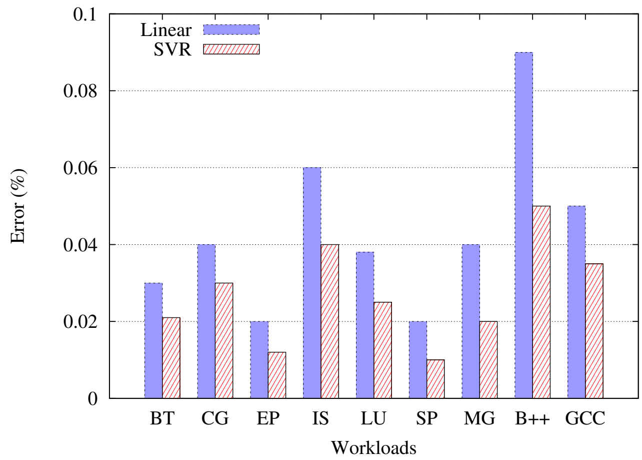

Figure 2. Mean absolute error of power prediction for a VM running various workloads

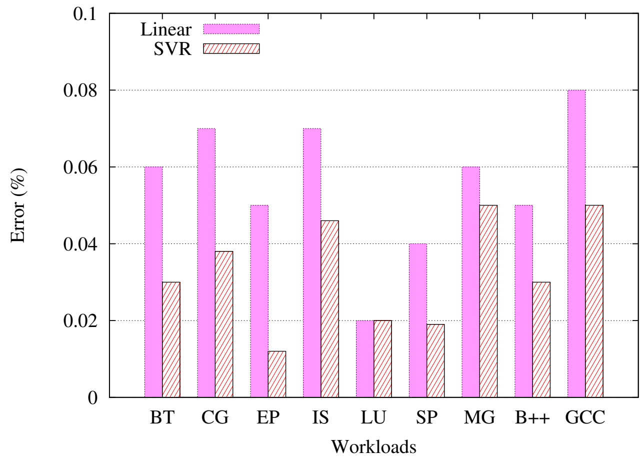

Figure 3. Mean absolute percentage error of power prediction for a VM running various workloads

for both linear and SVR prediction model under diverse workload scenarios and the results are shown in Figure 2 and Figure 3.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |P_m - P_p| = \frac{1}{n} \sum_{i=1}^{n} |e| \tag{7}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{|P_m - P_p|}{P_p} \tag{8}$$

where P_m is the measured power value using WattsUp pro power meter, P_p is predicted power value using SVR model and e is the error term. It can be observed from Figure 2 and Figure 3 that the proposed SVR model predicted the power consumption with the accuracy of 91% and 92%. Thus, the proposed SVR model is able to fit the data better than the linear model under various workload scenarios.

.

5. Conclusion

Measuring individual VM power consumption is an important and challenging problem in a shared virtualized environment. In this paper, a non-linear SVR based power prediction model using hardware PMC events has been proposed to predict the power consumption of an individual VM. Experimental results demonstrated the accuracy of the proposed approach in comparison with the existing linear based power prediction model. In future, the proposed model will be extended to include network sub component.

References

1. Armbrust Michael, Fox Armando, Griffith Rean, Joseph Anthony D, Katz Randy, Konwinski Andy, Lee Gunho, Patterson David, Rabkin Ariel, and Stoica Ion. A view of cloud computing. *Communications of the ACM*, 53:50–58, 2010.
2. Brown Richard, et al. Report to congress on server and data center energy efficiency: Public law 109-431. *Lawrence Berkeley National Laboratory*, 2008.
3. Kansal Aman, Zhao Feng, Liu Jie, Kothari Nupur, and Bhattacharya Arka A Virtual machine power metering and provisioning. *Proceedings of the 1st ACM symposium on Cloud computing*, ACM, 39–50, 2010.
4. Krishnan Bhavani, Amur Hrishikesh, Gavrilovska Ada, and Schwan Karsten. VM power metering: feasibility and challenges, *ACM SIGMETRICS Performance Evaluation Review*, 38:56–60, 2011.
5. Cherkasova Ludmila, and Gardner Rob. Measuring CPU Overhead for I/O Processing in the Xen Virtual Machine Monitor. *USENIX Annual Technical Conference, General Track*, 50, 2005.
6. Bohra Ata E Husain, and Chaudhary Vipin. VMeter: Power modelling for virtualized clouds. *IEEE International Symposium on Parallel & Distributed Processing, Workshops and Phd Forum (IPDPSW)*, IEEE, 1–8,2010.
7. Bircher W Lloyd, and John Lizy K. Complete system power estimation using processor performance events. IEEE Transactions on Computers,, IEEE, 61:563–577, 2012.
8. Bertran Ramon, Becerra Yolanda, Carrera David, Beltran Vicen, Gonzalez Marc, Martorell Xavier, Torres Juana, and Ayguade Eduard. Accurate energy accounting for shared virtualized environments using pmc-based power modeling techniques. *2010 11th IEEE/ACM International Conference on Grid Computing (GRID),* IEEE, 1–8, 2010.
9. Bertran Ramon, Becerra Yolanda, Carrera David, Beltran Vicen, Gonzàlez Marc, Martorell Xavier, Navarro Nacho, Torres Jordi, and Ayguadé Eduard. Energy accounting for shared virtualized environments under DVFS using PMC-based power models. *Future Generation Computer Systems*, Elsevier, 28:457–468, 2012.
10. Jiang Zhixiong, Lu Chunyang, Cai Yushan, Jiang Zhiying, and Ma Chongya. VPower: Metering power consumption of VM. *2013 4th IEEE International Conference on Software Engineering and Service Science (ICSESS)*, IEEE, 483–486, 2013.
11. Roberto Morabito. Power Consumption of Virtualization Technologies: an Empirical Investigation. arXiv:1511.01232, 2015.
12. Chonglin Gu, Shuai Shi, Pengzhou Shi, Hejiao Huang , Xiaohua Jia. Towards VM Power Metering: A Decision Tree Method and Evaluations. 15^{th} *International Conference, on Algorithms and Architectures for Parallel Processing (ICA3PP 2015)*, Springer, 508-523, 2015.
13. Oprofile: http://oprofile.sourceforge.net/news/
14. Iostat: http://ftp.at.gnucash.org/.vhost/linuxcommand.org/man_pages/iostat1.html
15. Xenoprofile: http://xenoprof.sourceforge.net/
16. WattsUp Meter: https://www.wattsupmeters.com/secure/index.php
17. NAS Parallel Benchmark: http://www.nas.nasa.gov
18. Bonnie++: Filesystem performance benchmark. http://www.coker.com.au/bonnie++/
19. GCC: GNU Compiler Collection. https://gcc.gnu.org/.