ARIMA-Based Aging Prediction Method for Cloud Server System

Haining Meng¹, Yuekai Shi¹, Yilin Qu¹, Junhuai Li¹ and Jianjun Liu²

¹ School of Computer Science and Engineering, Xi’an University of Technology, 5 Jinhua South Road, Xi’an, Shaanxi, China
² Aeronautics Computing Technique Research Institute, 15 Jinye Second Road, Xi’an, Shaanxi, China

E-mail: hnmeng@xaut.edu.cn

Abstract. Long-running software system tends to show performance degradation and sudden failures, due to error accumulation or resource exhaustion over time. This phenomenon is usually called software aging. Software aging is an important factor that influences software reliability. This paper presents a prediction method to investigate software aging in an OpenStack cloud system. At first, the performance data in an OpenStack cloud system is monitored and collected. Then, an autoregressive integrated moving averages (ARIMA) approach is used to predict the performance data. Finally, the experimental results and statistical analysis of collected data validate the presence of software aging in the OpenStack cloud system.

1. Introduction

In recent years, the rapid development of cloud computing technology brings the requirements on cloud-based applications into an extend area. The need for reliability, availability and performance has increased in cloud systems, which need to provide access to large pools of data and computational resources, and handle rapidly growing demands while providing uninterrupted services [1]. Moreover, multi-tenancy enables the sharing of resources and costs across a large pool of users [2]. However, the complex interactions between cloud service and multi-tenant application lead the cloud computing environment into the dynamic runtime scenarios, in which the long-running cloud system shows gradual resource consumption, reduced quality of service or even unavailable services, referred to software performance degradation [3]. Software performance degradation can be attributed to a steady accumulation of software faults which do not immediately cause a failure, but cause a sequence of damage to system and manifest themselves as memory consumption, unreleased file locks or data corruption etc., making the system gradually degrade its performance and finally fail. Software aging has been found in many kinds of systems in information field, such as telecommunication switching and billing system [4], database system [5], Apache web server [6], and cloud computing infrastructure [7].

By means of virtualization tools such as Xen, KVM and VMware, the virtualization technology is introduced in cloud computing to reasonably allocate software and hardware resources, which allows one or more virtual machines (VM) to be instantiated on a physical server (PM) through virtual machine monitor (VMM) to improve resource utilization. The emergence of cloud computing platform represented by Eucalyptus [8] has accelerated the research and popularization of cloud computing services. Araujo [9] configured different types of VM instances as workloads,
monitored the use of virtual memory and physical memory of the system, and detected the influence of workload changes on system aging. Matos [10] supposed that the I/O performance of cloud system is an important factor that affects the system execution time. By the intensive operation of connecting remote storage volume and generating VM instance, the aging process of system performance is accelerated, and the virtual memory and the physical memory is found to show an increasing trend. Langner and Andrzejak [11] found that the CPU usage of VM was gradually increasing, and the physical memory and swap area usage were gradually reduced, after that the HTTP request response on the VM was slow, resulting in the overall aging in the cloud system.

Software aging prediction forecasts the possible future degradation trend based on the historical performance parameter data of the software system. The prediction methods mainly include linear regression, chaotic theory, neural network, and particle filters [12-16]. In the cloud computing environment, Matos [17] proposed a time series prediction method based on multiple thresholds to solve the software aging problem in Eucalyptus cloud system. This method obtained the optimal rejuvenation time to reduce downtime and improve system availability. For amazon EC2 cloud system, Islam [18] adopted neural network and linear regression to predict the use of system resources and the method provides reference for resource allocation strategy. Kousiouris [19] adopted artificial neural network to predict the performance of VM in cloud systems.

In the area of cloud computing, cloud server controls large pools of compute, storage, and networking resources, which is the supporting runtime platform of web services, and the dynamic characters of web services affect systematic behavior and runtime state of cloud server. We study a OpenStack cloud server to see whether it suffers from software aging. Our final objective is to monitor system resources and predict the software aging, which plays an important role in improving the reliability and providing more reliable services for cloud end users.

The remainder of this paper is organized as follows. Section 2 describes the OpenStack system architecture with the aging prediction model. Section 3 presents the prediction approach based on ARIMA model. Section 4 shows experimental results to validate our proposed method. Section 5 concludes the paper and indicates future directions for research.

2. System architecture

OpenStack adopts a modular design mode and is mainly composed of seven components such as Keystone, Glance, Horizon, Nova, Swift, Cinder and Neutron, providing APIs, services and infrastructure resources to cloud end users. Figure 1 shows the architecture of a OpenStack server. Firstly, the workload generator is used to generate web service requests to the cloud server. Then, we monitor the utilization of resources for the entire system, specifically for the services Nova, Cinder. Afterwards, the system parameter data is collected and predicted by our proposed ARIMA method.

![Figure 1. System architecture.](image-url)
3. The aging prediction method based on ARIMA model

3.1. ARIMA model
The autoregressive integrated moving average (ARIMA) is an efficient statistical model for time series data to either better understand the data set or to predict future points in the series. This model is derived from one fundamental principle that the future values can be predicted using the white noise characteristics and the past values. The ARIMA($p,d,q$) model can be expressed mathematically as follows:

$$\phi(L)(1-L)^d n = \theta(L) \epsilon$$  \hspace{1cm} (1)

where, $p$, $d$ and $q \in \mathbb{Z}^+$, can be referred to as the order of AR, I and MA parts of the ARIMA model. $n$ refers to the input data, or, the observed points at time $t$. $\epsilon, t$ refers to the white noise at time $t$. $\Phi(L)$ are the lag polynomials, and $L$ is the lag operator. $d$ refers to the degree of ordinary differencing, it is used to make the time series stationary.

3.2. ARIMA-based aging prediction method

As shown in Figure 2, the time series data $\{N_i\}$ of the performance parameter index of the cloud server is firstly input, and the time series data is smoothed by the difference method. Then the ARIMA model is ranked by the ACF method and the PACF method. Afterwards, the values of

![Figure 2. Flow Chart of ARIMA-based aging prediction model.](image-url)
parameter p and parameter q are determined. At last, we perform residual test to obtain the final ARIMA(p,d,q) model. Finally, we predict the system performance of the cloud server and use RMSE for error analysis. The detailed prediction process is shown in Algorithm 1.

Algorithm 1. The proposed Cloud server VM performance prediction technique based on ARIMA

Inputs: The time series data \{N_i\} of the performance parameter index of the cloud server VM

Outputs: Prediction results and error values through ARIMA model

Steps:
1. Load the time series data of the performance parameter of the cloud server VM into \{N_i\}, d=1
2. if \{N_i\} is a stationary series
   do ARIMA model ordering
   else Differential processing for \{N_i\}, d=d+1
3. Ordering the ARIMA model
4. Use ACF and PACF to get the values of parameter p and parameter q
   //ACF: Autocorrelation coefficient;
   //PACF: Partial autocorrelation coefficient
5. Get model ARIMA(p,d,q)
6. Residual test   // Whether the ARIMA model is accurate through the test results
   if Residual test is inaccurate
   do Ordering the ARIMA model
   else prediction
7. Prediction processing
8. Output the predicted image and compare it with the original image
9. Error Analysis   // Use RMSE
j. End

4. Experiment results and analysis

4.1. Experiment Design

It is possible to accelerate the software aging process by adopting a stressful workload. Therefore what could take several months or even years, will take only a few days or depending on the aging severity, it may take hours. Some scripts of the workload characterization are used. Every five minutes the script is checked. The data used in this paper comes from the instance status of the OpenStack instance for a total of 10 hours from 21:00 on January 16, 2020 to 07:00 on January 17, 2020, which is obtained by continuously collecting the status data of the load instance. The load tool used in the example is sysbench, which includes CPU load, I/O load, memory load, disk load, and network load.

The experiments were conducted using OpenStack cloud platform which contained a variety of common items, such as computing services, mirroring services, database services, etc. In order to analyze possible aging effects in the OpenStack cloud computing platform, some python scripts were implemented and applied to our experiment. We use the scripts to monitor the utilization of resources. The data was collected every 10 seconds that is enough time to observe any important changes in the system behavior, such as CPU and memory consumption, we could also determine whether the resources were being consumed excessively. A part of the monitoring scripts focus on the general consumption of the hardware resources. That includes the consumption realized by all
the process in execution, threads and the operating system itself. While another part of the scripts aimed the resources consumption of the processes related to the OpenStack and the service provision. In this way we could identify a specific process that might undergo software aging.

The server system used for the experimental study is composed by one Intel(R) Core(TM) i5-4590 CPU four-core, 3.3GHz, 8 GB RAM, running the 18.04.1-Ubuntu x86_64 of the OpenStack cloud computing platform. The operating system running within the virtual machines is the Redhat 7.3 64-bit. The cloud environment under test is fully based on the OpenStack framework and the QEMU/KVM hypervisor.

4.2. Experiment Results

The time series that have been used, consists of OpenStack cloud platform Iowait dataset and memory dataset. The Iowait represents disk response time and is related to CPU usage. The Iowait time series were modeled using ARIMA.

The relationship diagram between Iowait and running time of OpenStack system is shown in figure 3. From the figure we could see that the overall Iowait time series shows a rising zigzag trend and the data rises gradually with time, which means the system response is steadily weaken. Some of the OpenStack processes are changing from the faster response rate to the slower ones. Thus it affects the whole performance of cloud system. Therefore, it can be concluded that the existence of software aging is evident in the OpenStack cloud server.
Figure 4 shows the result of the residual analysis process. From the results in the figure, we can see that the residual is a white noise signal, and the useful signal can be extracted into the ARIMA model.

![Residual Analysis Result](image)

**Figure 5.** One-step forward prediction for Iowait.

In figure 5, the blue curve depicts the original time series, and the red curve shows the single-step prediction time series. From the figure, it can be seen that the prediction trend basically coincides with the original data, which is the ideal prediction result.

![One-step Prediction Result](image)

**Figure 6.** Error between real data and prediction data.

Figure 6 shows the error results between the predicted value and the original value. As shown in the figure, the difference fluctuates from zero to the center line, and the error changes within the absolute value of 2, and the proposed prediction approach is more accurate.

5. Conclusions and future work

Aiming at a long-running cloud system subjected to software aging, we proposed an ARIMA based approach to predict the performance parameter. Based on our proposal, software maintenance could be adopted when the predicted data of resource consumption has exceeded a predetermined threshold. Numerical results have been shown to validate the effectiveness of the proposed approach.

In the cloud system, the indicators of performance degradation could be resource usage indicators (e.g., physical memory, virtual memory, swap space, cache memory) and performance...
indicators (e.g., response time or throughput). In this research, only the IOwait for CPU usage is taken in the experimental section. Future work will include more kinds of resource consumption and performance parameters of real data collected from the cloud system.

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