Software Aging in Image Classification Systems on Cloud and Edge

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***Abstract*—Image classification systems using machine learning are rapidly adopted in many software application systems. Machine learning models built for image classification tasks are usually deployed on either cloud computing or edge computers close to data sources depending on the performance and resource requirements. However, software reliability aspects during the operation of these systems have not been properly explored. In this paper, we experimentally investigate the software aging phenomena in image classification systems that are continuously running on cloud or edge computing environments. By performing statistical analysis on the measurement data, we detected a suspicious phenomenon of software aging induced by image classification workloads in the memory usages for cloud and edge computing systems. Contrary to the expectation, our experimental results show that the edge system is less impacted by software aging than the cloud system that has four times larger allocated memory resources. We also disclose our software aging data set on our project web site for further exploration of software aging and rejuvenation research.**

***Index Terms*—Cloud computing, Edge computing, Image classifiers, Machine learning, Software aging**

I. Introduction

Image classifiers using machine learning models are now pervasively deployed in consumer and industrial software systems. Recent advances in deep learning with evolved computation power enable highly accurate image classification in versatile application domains such as face recognition, surveillance systems, and autonomous vehicles [1]. To build an image classifier, a deep learning model is trained from image data sets on rich computing resources. The copies of the trained models can be used in software programs that receive image samples and output the classification results for the applications.

Depending on the requirements and constraints from the applications, image classifiers are deployed in either a cloud computing or an edge computer that is located near the data sources. The edge computer can be a stand-alone server, a small computer, or a smart device that is directly connected to an image sensor (e.g., camera). Compared to the cloud computing that offers scalable computing resources on demand, the edge computers have limited resources that may not be sufficient for image processing [2]. On the other hand, the network connection and the communication bandwidth tend to be the bottleneck of cloud computing, especially for latency-critical applications such as connected car [3]. Existing studies for edge computing discussed when and how to allocate computing tasks between cloud and edge considering the performance and resource requirements [4]. However, little has been explored on the software reliability aspects during the operation, in particular for continuously running software programs dealing with image classification tasks.

In this paper, we experimentally evaluate the software aging phenomena in image classification systems continuously running on cloud or edge computing environments. We examine how software aging phenomenon appears differently between these two environments. In the experiments, we used the MNIST data set [5] that contains hundreds of handwritten images of digits from 0 to 9. The image classifier is trained from the training data set offline. The software program employing the trained classifier is deployed on either a cloud or an edge system on which classification tasks are executed continuously in response to the image samples sent from a client. For different architecture options (i.e, either the cloud or the edge) and different workload intensities, we collected system performance metrics for 72 hours. Using Mann-Kendall test [6] with Sen's slope estimate [7], we confirmed the increasing trends in the memory consumption both in the edge and the cloud systems. In high workload case for the cloud system, we observed a system failure due to the depletion of memory. Contrarily to our expectation, the experimental results indicate that the image classification system on the cloud has a more significant impact by software aging. Although the results cannot be generalized easily to other applications, our observation implies that we may not always assume that cloud is more robust than edge computing against software aging. Since the manifestation of software aging highly depends on software stacks under the executed program, the amount of available resource does not guarantee the safe execution of long-running software programs. Our data analysis provides only a preliminary result, and further analysis is required to identify the software aging problem. To open further studies on software aging and rejuvenation in cloud and edge computing systems, we provide our data set online [8] that can be used for research purpose.

The rest of the paper is organized as follows. Section II describes the related work for software aging analysis. Section III explains our experimental plan in detail. Section IV shows the experimental results with some statistical analysis. Section V presents our conclusion.

II. Related Work

Studying software aging in cloud-based systems is becoming increasingly important because of the negative impact that a problem can have both on user-perceived quality of services (e.g., availability, reliability and performance) and, consequently, on the huge market around cloud-based systems and services. There is an increasing interest from the Software Aging and Rejuvenation (SAR) community in analyzing the phenomenon in cloud-based systems. A recent survey reports almost one hundred papers in the last ten years with a considerable number of research groups around the world addressing this topic [9].

A considerable number of papers investigate SAR in the cloud, or more generally in virtualized systems, by exploiting stochastic models such as stochastic Petri nets (SPN) and stochastic reward nets (SRN) [10]–[13], continuous-time Markov chains (CTMC) [14], [15], semi-Markov processes (SMP) [16], [17], as well as combinatorial models such as reliability block diagrams (RBD) [18] and dynamic fault trees (DFT) [19]. In these works, the cloud architectures – including virtual machines (VMs), virtual machine monitor (VMM), and physical host(s) - and the associated rejuvenation strategies are modeled with the aim of computing the optimal time for rejuvenation and of fine-tuning the adopted rejuvenation techniques.

Many other researchers considered a measurement-based strategy, which is the same approach we adopt in this work. Statistical techniques for time series analysis of indicators of interest (such as response time and memory/resource consumption) is the most common approach. For instance, the work by Araujo *et al.* characterize the aging phenomenon on the Eucalyptus cloud computing framework [20]. That work adopts several regression models including linear, quadratic, exponential growth, and Pearl-Reed logistic models to predict memory consumption trends and schedule software rejuvenation properly. Sukhwani *et al.* analyze the aging of IBM cloud controller systems with a similar strategy [21]. Umesh *et al.* also exploit time series models to forecast software aging patterns of Windows active directory service for virtualized environments [22].

Mohan and Reddy study the effect of aging on an uncommon, but very important indicator for cloud computing, namely energy consumption [23]. The authors exploit linear regression to estimate the trend. Energy consumption is also considered by Villalobos *et al.* [24], where an IDS-based self-protection mechanism at the virtual machine level inspired by software rejuvenation concepts is presented. A correlation between IDS accuracy, attack rate, cloud system workload, energy consumption, and response time is identified – in fact, security-related aging problems are also of increasing interest. The work presented in [25] performs a workload-dependent analysis of performance degradation and memory indicators in Apache Storm, an event stream processing (ESP) application, deploying tasks over a cloud architecture, by means of workload-dependent time series analysis. In addition to time-series analysis, machine learning strategies have also been used in cloud-based systems or cloud applications to detect/predict the possible aging system state (e.g., [26] [27] [28]), as well as the simpler threshold-based approach on specific aging indicators [29] [30].

In this work, we focus not only on aging at cloud level but also explore aging in an edge-computing scenario. Deploying physical resources and distributing computational efforts following a different architectural style, such as in the edge computing paradigm, can have effect on the overall performance degradation perceived by the end user. Moreover, to the best of our knowledge, the task we consider as application, namely machine-learning-based image classification, is also unexplored from the SAR perspective. We hereafter show whether this task is able to expose aging phenomena in the underlying cloud-based and edge-based architectures.

III. Experimental Plan

A. Research questions

The objective of our experimental study is to investigate potential software aging issues in image classification systems running on cloud or edge. If there is symptom of software aging, it is also interesting to see the difference of its manifestations between cloud and edge systems. Therefore, we raise the following research questions for our experimental study.

- RQ1: Does an image classification system executing on a cloud encounter any software aging problems? and, if it does, how significant it is, and what is the cause?
- RQ2: Does an image classification system executing on an edge computer encounter any software aging problems? and, if it does, how significant it is, and what is the cause?
- RQ3: Does the image classification system executing on an edge computer have a higher impact by software aging than the same system executing on a cloud?

To answer these questions, we conducted the following experiments.

B. Setup

As an application of an image classification system, we consider a handwritten digit recognition task. We use the MNIST data set [5], which consists of images of handwritten digits from 0 to 9. It has 60,000 training images and 10,000 test images. This data set is a well-known benchmark for image classification. The challenge with this data set is to correctly classify a handwritten digit based on a 28-by-28 black and white image. We implemented a Python program that employs a neural network to recognizes handwritten digits. In this system, images are generated and sent from a client's device over the network to a server for image classification on a continuous basis. Note that the input of the image classification system is a 784 size vector, obtained from converting the image, originally a 28x28 size matrix, to a 784 position vector.

To create the neural network, we used Keras' Sequential API [31]. The network consisted of three layers with 64 filters each, using the Rectified Linear Units (ReLU) activation. The

output layer is a Dense layer with 10 nodes and Softmax activation function. Dropout with probability of 0.2 was used on the fully connected layers. We compiled the model with categorical_crossentropy loss and the adam optimizer. We trained the model with the training data set for a total of 20 epochs, and then we used the model for image classification on the server side.

We prepared two testbed systems for the experiments; i) cloud computing system and 2) edge computer system. The cloud computing system consists of a client device and a virtual machine executing the image classification system hosted on Google's cloud infrastructure. Image samples to be classified are uploaded from the local client to the virtual machine periodically. On the other hand, the edge computer system consists of a client device and an edge computer that executes the same image classification program. The generated image samples are sent to the edge computer via a wireless local area network. In the both testbed systems, the client device plays as a workload generator, which is a program written in Python 3 to generate constant workload. The specifications of the system components are given as below:

- Client device: Apple MacBook Air 11-in, Intel Core i5 1.60GHz, 4 GB, 64 GB, Mac OS X Lion 10.7.
- Virtual machine: n1-standard-1 (1 vCPUj, 3.75 GB of memory), Debian GNU/Linux 10 located in us-central1-a.
- Edge: Raspberry Pi 3, 900MHz quad-core ARM CPU, 1GB RAM, running the default Raspbian Linux image.

C. Experiments, metrics, and analysis method

To address the research questions, we conducted two sets of experiments. The first set aims at investigating the possible presence of software aging in the image classification system running on the cloud. To this end, we used our cloud computing testbed and applied the following workloads: no workload, low workload (1 image every 1 second), medium workload (1 image every 0.5 seconds) and high workload (1 image every 0.1 seconds). For each workload setting, we executed the experiments for 72 hours. The second set aims at investigating the possible presence of software aging in the image classification system running on the edge computer. We uses the edge testbed and applied the same workload.

For each experiment, we collected system monitoring data and analyzed aging indicators. The aging indicators refer to the system variables that can be directly measured and can be related to the software aging phenomena [32]. The analysis of aging indicators can be performed both at system level and application level. System level analysis investigates a potential software aging phenomenon in system resources. On the other hand, the application level analysis aims to identify the processes more responsible for resource consumption and user-perceived performance degradation, if any. In this work, we considered the aging indicators in both of the user-perceived performance and the resource depletion in terms of real memory consumption. As stated in [33], these are the typical aspects considered in software aging studies. Regarding the user-perceived performance, we adopted the mean response time, which is the mean time from sending the image to the end of image processing.

For statistical analysis to detect potential software aging phenomena, we adopted the conventional Mann–Kendall test (MKT) [6] to analyze the trends of aging indicators, and the Sen's slope estimate [7] to calculate the magnitude of the trends. The Mann-Kendall analysis checks the null hypothesis (H0) that there is no trend in the time series data, while the alternative hypothesis (H1) indicates an upward or a monotonic downward trend in the data. If the p-value of the test is lower than the significance level (α =0.05), then there is statistically significant evidence that a trend is present in the time series data. As software aging is a cumulative process, the MKT can be used to reveal patterns of software internal state degradation. It should be noted that the trend detected by MKT does not directly mean the existence of software aging [34]. However, system encounters a system failure or significant performance degradation after long time execution, the observed trend of resource usage likely indicates the existence of software aging. On the other hand, Sen's slope is the statistic to measure the magnitude of the trend. It is computed as the median of all pairwise slopes between each pair of points in the data set so that a positive Sen's slope implies a positive trend, while a negative Sen's slope means a negative trend.

IV. Result Analysis

In this section, we present the results of experiments and statistical analysis we conducted for two testbed systems.

A. Results from the cloud environment: RQ1

For the image classification system running on the cloud, we observed software aging issues both in the response time and in the memory usages. Figure 1 plots the measured response times for the image classification system by different workload settings. The horizontal and vertical axes represent the experimental time and the observed response times, respectively. The results clearly show the response times are affected by the workloads of image classification tasks. In particular, we observed a surge in the response time for the case of high workload after 10 hours of execution. At this time, the virtual machine was crashed. For the middle workload case, on the other hand, we observed the characteristic behavior of the response time that had two peaks in the observation period. After reaching the first peak around 18 hours, the response time decreases slowly, but it jumps up again around 56 hours. In total, the response time is getting worse. For the low workload case, the response time is relatively stable, although it can be observed a slightly increasing trend.

In Figure 2, we show the traces of memory usages in the cloud VM under the different workloads: (a) None, (b) Low, (c) Middle, and (d) High. For all the cases including no workload case, we observe the increasing trends in the memory usage. For the high workload case, the memory usage reached

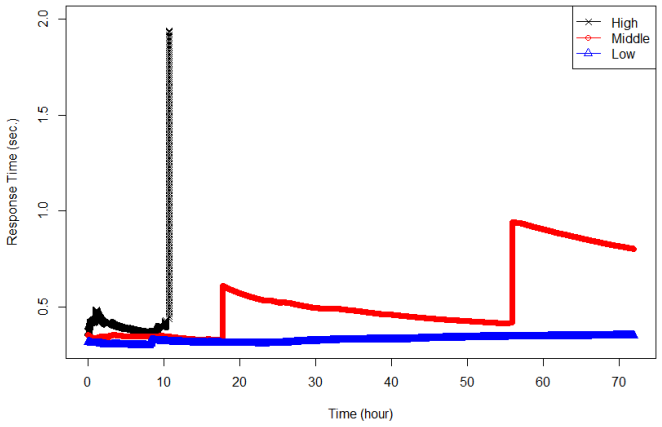


Fig. 1: Response time for the image classification system on the cloud testbed.

TABLE I: Sen's slope estimates for the cloud memory usage data in different workload settings at 95% confidence level with confidence intervals.

Workload	Slope estimate (MB/hour)	LCI	UCI
None	5.871991e-04	5.439642e-04	6.309148e-04
Low	5.345212e-04	5.034965e-04	5.658627e-04
Middle	1.5831818	1.53600	1.63016
High	5.7149268	5.689639	5.760805

the maximum capacity of the VM around 10 hours at which the VM is restarted by the cloud infrastructure. Similar behavior was detected in the middle workload case, but the memory was not released because it did not reach the maximum memory capacity.

We conducted the statistical analysis on the measured time-series data. For Mann-Kendall test, the p-values are less than 0.05 for all the cases, leading to the conclusion that the null hypothesis is rejected. In order to compare the significance of trends, next we applied Sen's slope estimator. Table I presents Sen's slope estimators for cloud memory usages under different workloads with the Lower Confidence Interval (LCI) and Upper Confidence Interval (UCI) at 95% confidence level. For high and middle workloads, we only considered the data until the first peak points. The results showed that the slope becomes steeper as the intensity of the workload increases.

In order to further investigate the underlying causes of the suspected aging phenomenon, we performed a process analysis for the VM on the cloud. We created a program in Python 3 to gather information about the processes running on the system every hour. This program uses the `ps` command[1] with `eo` to retrieve process information from particular columns like Process Identification Number (PID), Resident Set Size (RSS), and Virtual Set Size (VSZ). Our analysis indicated that two main process were responsible for the increase in the memory consumption: "tmux" and "systemd-journald". Tmux is a terminal multiplexer, while systemd-journald is a system service that collects and stores logging data. In the experiments, tmux was used to keep the system running regardless of the cloud SSH connection. Although tmux is not the main part of the image classification system (rather it is part of the experimental configuration), the memory consumption was affected by the workload intensity of image classification tasks. If this causes a failure like the one observed in the high workload case, it is not a negligible issue. To locate the root-cause, we need more deep investigation on the dependencies of related software components.

[1]The ps command is a traditional Linux command to lists running processes.

B. Results from the edge environment: RQ2

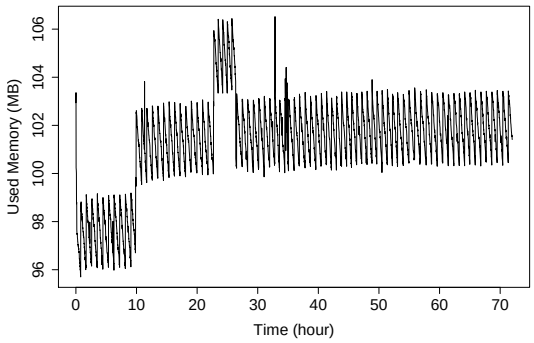
To answer the RQ2, we deployed the image classification system on our edge system and performed the same workload tests. Figure 3 shows the observed response times of the system by different workload settings. In contrast to the results from the cloud system, we do not see clear increasing trends of the response time regardless of the workload intensity. For the high and low workload cases, the difference is almost negligible especially after 20 hours (the difference is less than 0.01 second). The response time for the middle workload case, however, is consistently worse than the others (about 0.02 seconds longer than the other cases after 35 hours). We suspect this small difference was caused by a temporal congestion of local area network traffic.

In Figure 4, we show the traces of memory usages in the edge computer under the different workloads: (a) None, (b) Low, (c) Middle, and (d) High. As can be seen, the results highlight the trends on memory consumption for all workloads, even in the no workload case. The results of Mann-Kendall test for these memory usage data showed the p-values were less than 0.05. Thus, the null hypothesis is rejected, indicating that there are trends in the data. We also applied Sen's slope estimator to compare the significance of trends among different workloads. Table II shows Sen's slope estimates for edge memory usages, including the lower and upper confidence intervals. The results show that higher workloads cause the steeper slopes of memory usage trends. The increasing trends in memory consumption can be benign process that is not caused by software aging. However, as we observed that the trend slope has a positive correlation with the workload intensity, there is potentially software aging issue associated with the workloads of image classification tasks.

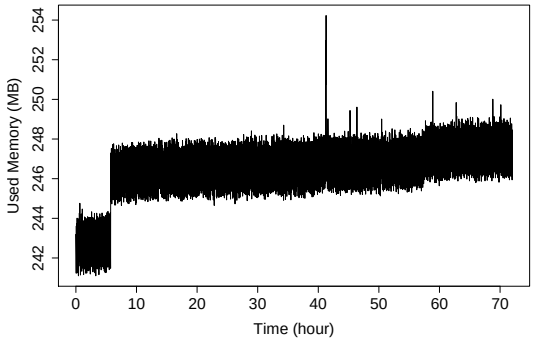
TABLE II: Sen's slope for estimates for the edge memory usage data in different workload settings at 95% confidence level with confidence intervals.

Workload	Slope estimate (MB/hour)	LCI	UCI
None	1.883117e-03	1.871147e-03	1.895147e-03
Low	1.962545e-03	1.950317e-03	1.974779e-03
Middle	1.984127e-03	1.971902e-03	1.996338e-03
High	2.078947e-03	2.060263e-03	2.097693e-03

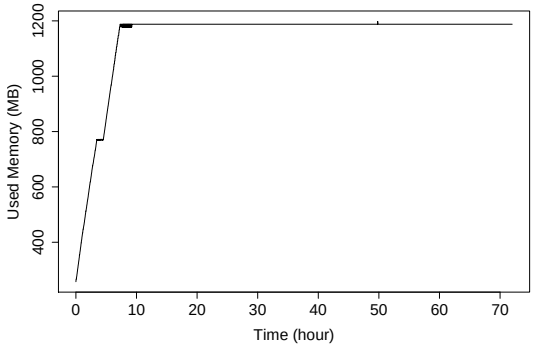
In order to understand the underlying causes of the increasing memory trends, we performed the process analysis for identifying the processes that are eating the memory of



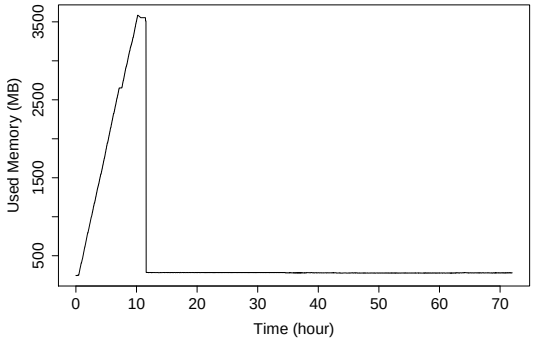
(a) None workload



(b) Low workload



(c) Middle workload



(d) High workload

Fig. 2: Cloud memory usages considering the following workloads: (a) None, (b) Low, (c) Middle and (d) High.

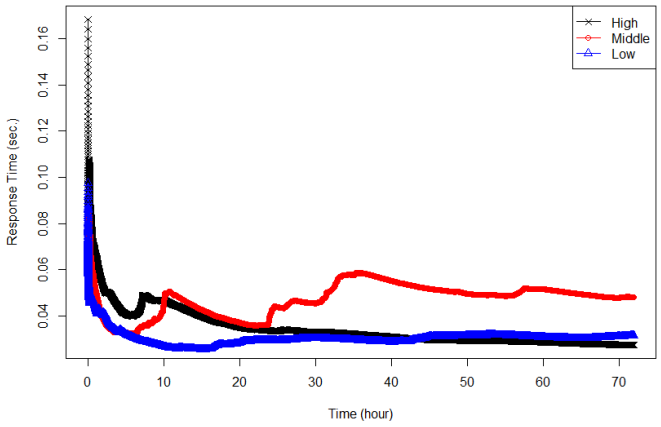


Fig. 3: Response time for the image classification system on the edge testbed.

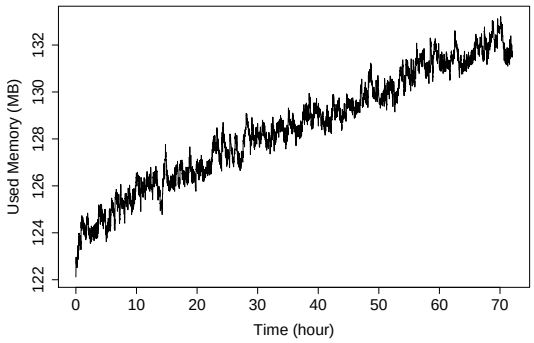
edge computer. Our analysis indicated that two main process were responsible for the increase in the memory consumption: "hwrng" and "systemd-timesyncd". The former is a library for random number generation, while the latter is a daemon used for synchronizing the system clock across the network. Although these processes are not the part of the image classification tasks, there can be software dependencies causing the increased memory consumption in response to image classification workloads.

C. Comparison between cloud and edge: RQ3

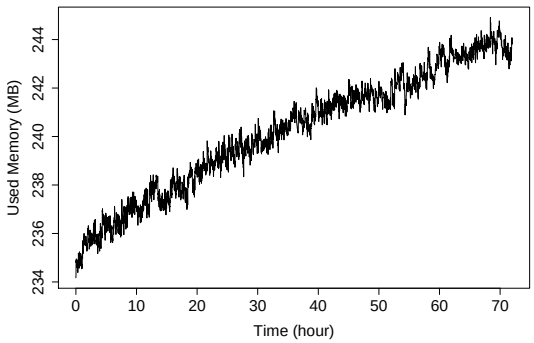
From the obtained results, we cannot state that an edge computer is more impacted from software aging than a cloud environment which has more computer system resources. In fact, our experimental results showed a counter-intuitive fact that the edge system provides more robust execution environment for the image classification system than the cloud system. For our experimental settings, the allocated memory for the cloud was about four times higher than the memory available on the edge (3.75GB vs. 1GB). With numerous interdependent and tightly coupled components, cloud-based environments can lead to aging gaps and make it difficult to find the underlying causes of this phenomenon. Additionally, as expected, the edge had a better performance than the cloud. For instance, if we consider high workload, the edge had, on average, a response time 17 times faster than the cloud.

V. Conclusion

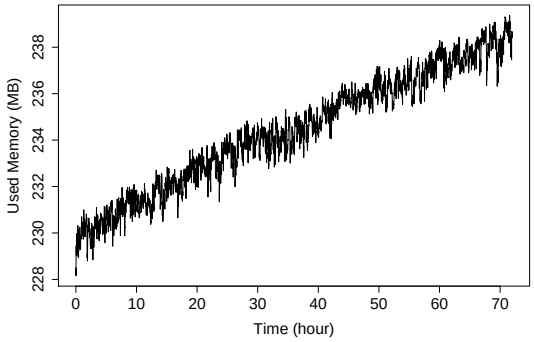
In conclusion, we observed that the manifestation of software aging in image classification tasks had quite different characteristics between cloud and edge computing environments. In our test application program, software aging has a significant impact on the cloud environment rather than edge computing systems with less amount of resources. This could be just an instance of complex environment-dependent



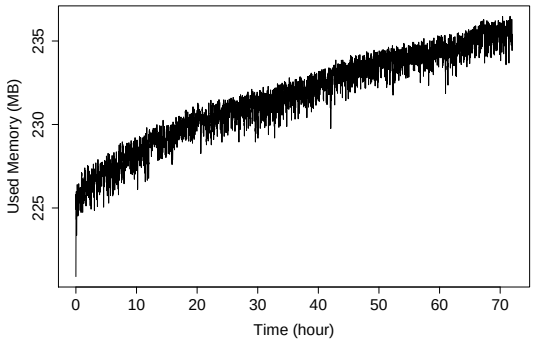
(a) None workload



(b) Low workload



(c) Middle workload



(d) High workload

Fig. 4: Edge memory usages considering the following workloads: (a) None, (b) Low, (c) Middle and (d) High.

software aging problems among cloud, fog and edge computing architectures. Software aging experiments are essential to understand the actual software aging impacts on different software stack and to determine the right place to deploy the classifier in terms of software system reliability.

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