Study on High Availability and Fault Tolerance

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***Abstract*—Availability is one of the most important requirements for modern computing systems. It defines the maximum acceptable outage time for any given period. In cloud computing, it is common to use it as a key factor to adopt a cloud service. This paper studies the breakdown in calculating the availability and proposes a conceptual model as middleware in order to speed up the time for detection during a system crash. Through simulations tests, we verified that the proposed model is able to detect the system crash in sub-seconds and improve the overall availability of the system compared to currently used industry solutions.**

***Index Terms*—availability, cloud computing, docker**

I. Introduction

Remote working and e-commerce have become the new normal since the pandemic [3, 10], they have changed our daily lives and the way how we consume services. With the growth of these online services, there is a high demand for non-functional requirements, especially in the domain of Availability and Fault Tolerance.

Availability [11] is considered one of the main challenges of modern IT, especially for cloud computing since it can provide dynamic elasticity on computing resources. Therefore, as more missing critical applications are shifting towards this architectural pattern, availability has been considered one of the major concerns.

High Availability defines the maximum allowed outage time, which usually refers to ”5-nines” of up-time, i.e. less than 6 minutes of downtime annually [2]. On the other hand, we have Fault Tolerance. It means that the system will operate continuously even if some of the components fail. Instead of failing completely, applications are designed to operate at downgraded service, while system recovery will take place and try to resume the service automatically.

This paper will examine the current service availability and fault tolerance in cloud providers’ practices, together with other proposed solutions in other research papers and industry best practices. Finally, we will try to propose a system design that aims to improve service availability and fault tolerance with a sample implementation.

The organization of this paper is as follows. In Section 2, we will discuss the related works with various definitions of availability and fault tolerance used. We will then introduce the current challenges in Section 3. In Section 4, we will propose and implement our novel solution using a sample application. Evaluation and performance assessment is conducted in Section 5, followed by a summary and conclusions.

II. Related Works

Understanding what availability is a prerequisite for the evaluation. The term ”Availability” was defined as ”the degree to which a system is functioning and is accessible to deliver its services during a given time interval” [6]. This is the percentage of time that allows outage time for a given period. Some researchers further defined availability in the form of Service Level Agreements [5], and considered availability as the ”probability of providing service according to defined requirements”.

This term has been extensively used by service providers, especially cloud service providers [4]. In case any hiccups cannot fulfill this commitment, service providers will even issue credit for compensation [1]. Therefore, a lot of research effort has been dedicated to guaranteeing availability in the cloud [8].

In the domain of cloud computing, [13] has proposed the cloud availability taxonomy using three criteria: availability mechanisms, failures protected against, and metrics, which categorized all the redundancy models accordingly Availability Management Framework [9]. We define ”High Availability” as a service that is available at least 99.999% of the time [6]. For example, the maximum downtime under this scenario for service annually is only 5 minutes and 15 seconds.

In 2010, [14] proposed a middleware ”Low Latency Fault Tolerance” that uses different protocols for membership, messaging, and synchronization to achieve fault tolerance at the application level. This middleware provides fault tolerance for distributed applications using the leader/follower replication approach. In 2011, [13] proposed a ”heartbeat” approach to detect application failures. When there is no heartbeat received within a grace period, it is assumed that the application has failed and fail-over/recovery action will be triggered. For instance, the AWS load balancer monitors [12] the application status in such a way, but they do not protect against application failures. Although this mechanism does not detect all possible application failures, it is the most generic way as the application team is only required to provide an HTTP endpoint. However, this heartbeat technique is not an effective solution since it is a passive pull-based mechanism that takes more than 10 seconds to detect the failure. Finally, with the rise of microservice architecture, some researchers have begun to use Docker / Kubernetes to achieve better availability by shortening the reaction time to detect fault events [14].

As mentioned before, we will explore all the available

mechanisms in this paper and propose our own novel solution that allows for the higher availability of cloud resources.

III. Problem Statement

In layman's definition, the availability can be expressed by a mathematical equation :

$$Availability = \frac{uptime}{uptime + downtime} * 100\%$$

The higher number will have better availability, which provides better service level agreement.

To further understand the problem, we can further define Reliability as the probability that a system continues to work as expected over a specified time duration. Thus, the terminology MTBF (Mean Time Between Failures) is used to represent the average time to the next failure, and is calculated as:

$$MTBF = \frac{Service\ Running\ Duration}{Number\ of\ Incidents}$$

This MTBF is not only used in Computer Science, but it is also widely used as an important maintenance metric to measure performance, safety, and equipment design for mission-critical systems [7]. Another point to note is that MTBF only considers unplanned maintenance time, while planned maintenance events like scheduled software updates are not included.

Another term related to availability is MTTR (Mean Time To Recovery) which is the total duration starting from system malfunction, system detection and system recovery, which is denoted as

$$MTTR = \frac{Mean\ Time\ to\ Recovery}{Number\ of\ Incidents}$$

Based on MTBF and MTTR definition, the availability of a system can be used to measure the impact of failures on an application, and the availability can be defined as:

$$Availability = \frac{MTBF}{MTBF\ +\ MTTR} * 100\%$$

where we can further break down MTTR as:

$$MTTR = MTD + MTF$$

where:

- MTD = Mean Time to Detect
- MTF = Mean Time to Fix

Hence, we can express availability as a function of:

$$Availability = \frac{MTBF}{MTBF\ +\ MTD\ +\ MTF} * 100\%$$

The relation between all of those above is presented in Figure below.

Therefore, using the formula above, we can improve the Availability by either increasing the Service Up-time (maximize MTBF) or decreasing the Mean Time to Detect (minimize MTD) or decreasing the Mean Time to Fix (minimize MTF), which we will discuss in the subsection below.

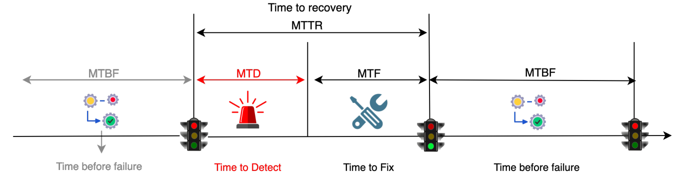

Fig. 1. Illustration on the relationship between various status

A. Optimization problem

The primary objective is to maximize the Availability of a system in order to achieve higher Service Level Agreements (which means more ninth). Thus, we can either perform:

1) Maximize the MTBF: There are a number of ways to increase the MTBF. For example, keeping track of the MTBF for each sub-system, especially those long-run operation processes. Perform machine learning/data mining techniques to identify any usage pattern that will lead to system failure, then arrange corresponding fixes during planned maintenance. While this can improve the MTBF and result in better availability, this paper will focus on how to minimize the denominator, i.e. to minimize MTTF in order to improve the overall availability.

2) Minimize Time to Detect (MTD): By Murphy's Law: "Anything that can go wrong will go wrong". While we could not completely eliminate the chances for system failures, we should try to minimize the time to detect the error such that we can discover the problem earlier in order to shorten the total time of the outage. Then the overall availability will be increased.

3) Minimize Mean Time to Fix (MTF): By standardizing the procedure to restart/repair or replace the faulty component, the time to fix the problem can be reduced. On the other hand, by reserving additional spare components as redundancy, the time to repair can be minimal, providing that the failure cause is not due to logical fault. In this paper, the application we implemented will make use of Docker and Publish/Subscribe mechanism to speed up the recovery.

IV. The algorithm

As we have discussed in the previous section, we will focus on minimizing the "Time to Detect" and "Time to Fix". The industry practice is to use pull-based health checks, i.e. load balancer that keeps sending probe requests to each worker node every interval (t_h). In case the worker node is unavailable immediately after the last health check, then the particular worker node will become unavailable until the load balancer detects it in the next health check $2t_h$. To make things even worse, the system will send additional retry health checks which means that the outage time can be up to $3t_h$. Therefore, in this section, we propose a push-based health-check mechanism such that the system can detect node availability as earlier as possible.

Before we describe the algorithm, we introduce its components in Figure **??**

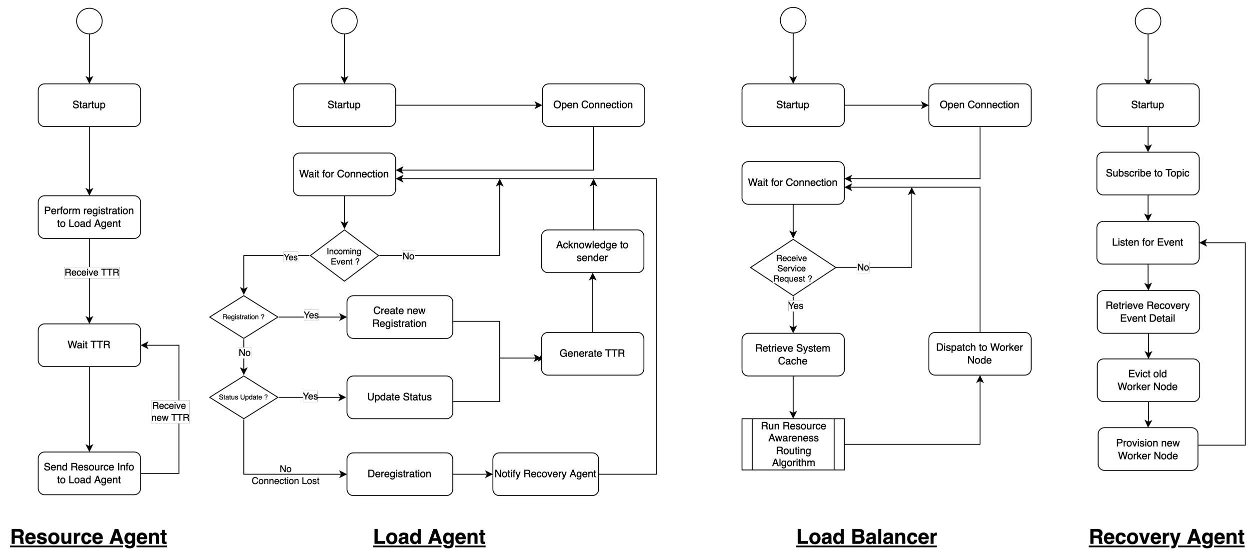

Fig. 2. High-level overview for each individual component

A. Resource Agent

This is an embedded agent running on the worker load. When the worker node startup, it will register an ”Alive” signal to the Load Agent. Once connected, it repeatedly sends a ”Status Update” event which includes the CPU/Memory/Storage/Active thread count to the Load Agent and expects to receive an acknowledgement with ”Time To Repost” (TTR). Then the agent will wait for this TTR and send the updated resource information again.

B. Load Agent

This is a standalone agent running independently from the service application. This daemon starts a socket and waits for connections from Resource Agent. Then it will keep a persistent session which expects to receive a ”Status Update” from Resource Agent. Then, it will update the status of the Resource Agent into a distributed cache such that the Load Balancer will use this information for client request dispatching. Since the connection is a socket connection, in case the connection is lost, this persistent connection will be terminated and the Load Agent will be notified immediately, then it will detach this worker node from the cache, such that the Load Balancer will not dispatch the client request to this crashed node accordingly. In order to enhance the fast recovery, this agent will also publish a recovery message such that Recovery Agent will perform recovery action accordingly.

C. Load Balancer

This is the client-facing endpoint that accepts external requests. Then we implement a Resource Awareness routing algorithm to select a worker node, then dispatch the request to this node to handle. In case there is no node available, we will report an outage and advise the client to retry later.

D. Recovery Agent

This is another standalone agent that works like Kubernetes master node to perform worker node life cycle management, including node creation and eviction. This agent subscribes to the topic that Load Agent will publish recovery requests in case any worker node was crashed.

E. Resource Aware Routing Algorithm

Our approach is a greedy algorithm that will select nodes that match several criteria. We named it Resource Aware Routing Algorithm (RARA). The highest priority will be finding a worker node that has available resources that are ”Just Fit”, which means after servicing this new request, this node will be saturated. The rationale is that we would like to reduce resource fragmentation across different worker nodes. In case we can fill up the capacity for one particular node, then we can keep other resourceful nodes for future demanding requests. In the meanwhile, we proposed a thread level checking to ensure that the number of concurrent thread cannot be greater than the average, such that no worker node will be too heavily overloaded while some node is deep underloaded. However, this is subject to the programming language and the system’s capability. The pseudocode is available in Figure 3. Furthermore, the entire flow of the system is shown in Figure **??** - when Worker Node A disconnects, Load Agent will receive a ”Session Disconnection” signal, then it will immediately update the system cache, so the subsequent client request will not route to this faulty node accordingly. In the meanwhile, the Load Agent will also trigger a ”Recovery” message to Recovery Agent to perform the worker node eviction and re-provision.

The proposed methodology considerably enhances Availability since it uses the persistent connection with push-based health checks. In the traditional pull-based health check by

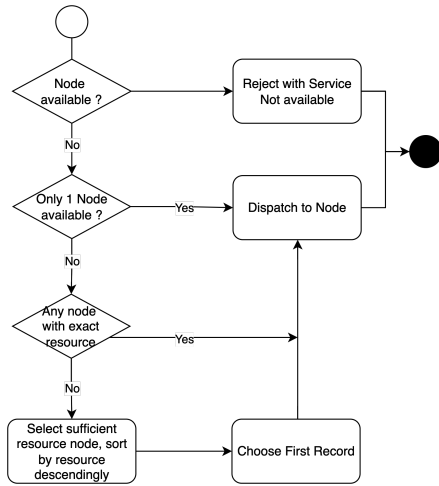

Fig. 3. Resource awareness routing algorithm (RARA)

Load Balancer, each probe requires a new TCP connection such that it will spend extra time on TCP handshaking. By using the persistent connection, the Load Agent will receive a "Session Disconnect" signal immediately when any worker node crashes. Therefore, the "Time to Detect" is expected to be much shorter than the pull-based mechanism. However, the drawback is persistence push-based mechanism will consume much more system resources than the pull-based, so this methodology should be used on mission-critical or computing/networking resources in abundance applications.

In the next section, we will discuss our sample application that uses this stack and compare it with the Amazon Application Load Balancer accordingly.

V. Simulation Plan

The proposed architecture was constructed, as shown in Figure 5, and we compared it with the standard, out-of-box Amazon Load Balancer.

For evaluation purposes, we have implemented the entire application using Nodejs. Socket.io was chosen as the persistent connection middleware between Resource Agent and Load agent. Redis was adopted as the cached layer and also Redis pub/sub were adopted for the communication between Load Agent and Recovery Agent.

In order to demonstrate the Resource Agent middleware, various workload applications that embedded this agent were built and further dockerized as a Docker image, such that the Recovery Agent can perform recovery by using the docker command. Since we are trying to measure the performance of fault detection, we embedded a "Kill Switch" that will trigger the application to "crash" after providing service for a particular time.

Finally, the ELK stack was selected as the log management layer such that we can capture all the status log centrally.

In this paper, we analyze the performance of the existing cloud provider fault-detection method and the proposed fault-detection method via experiments. Subsequently, we compared how the performance varies depending on the change in workload and resource usage. We set up 10 threads to run 1,000,000 iterations per scenario.

We will perform the simulation using a different workload against kill switch frequency.

VI. Analysis

A. Mean Time To Detect

We calculated that the average time to detect a system crash is around 24.5 milliseconds. The data is consistent across lightweight web service tasks and I/O-bound tasks. The reason is that these jobs did not affect our proposed algorithm since the Kill-Switch mechanism is running independently in the NodeJS event loop. However, the CPU-bound jobs were greatly affected since NodeJS is a single-thread programming model, which means that only one task can be executed at a time. Our implementation tried to compute the Fibonacci series so the JavaScript engine would execute the computation solely so our resource agent plugin was "paused" during execution. Therefore, we have dropped out the CPU-bound jobs testing after several trials runs.

Compared with the AWS application load balancer, the theoretical "time to detect" is 14 seconds. This figure is calculated based on the AWS Target Group Health Check setting, the minimum. The minimum unhealthy threshold is 2, while each health check interval takes 5 seconds with 2 seconds timeout. As illustrated in Figure 6, the worst case mean time to detect is (5+2)* 2 = 14 seconds. Therefore, our proposed approach (24.5 ms) is 570 times faster.

B. Overall Service Level Agreement

Instead of focusing on the Mean time to detect, we focused on the effectiveness of the overall service level agreement.

TABLE I
Detail breakdown of the simulation

#	Duration(s)	Up(s)	Down(s)	SLA(%)	Fail Count
AWS kill-switch 5	2,105.901	2,020.234	85.667	95.93204%	2,080
AWS kill-switch 10	2,203.670	2,131.404	72.266	96.72067%	1,518
AWS kill-switch 20	2,089.374	2,048.838	40.536	98.05992%	1,021
RARA kill-switch 5	2,943.944	2,936.602	7.343	99.75058%	3,990
RARA kill-switch 10	2,970.906	2,970.883	0.023	99.99923%	600
RARA kill-switch 20	3,005.539	3,004.165	1.374	99.95429%	308

In our proposed solution, as we run in a local environment, we created 10 threads that triggered 100,000 requests individually, so the total execution is 1 million requests for each kill switch iteration. The total execution time for each iteration is around 50 minutes.

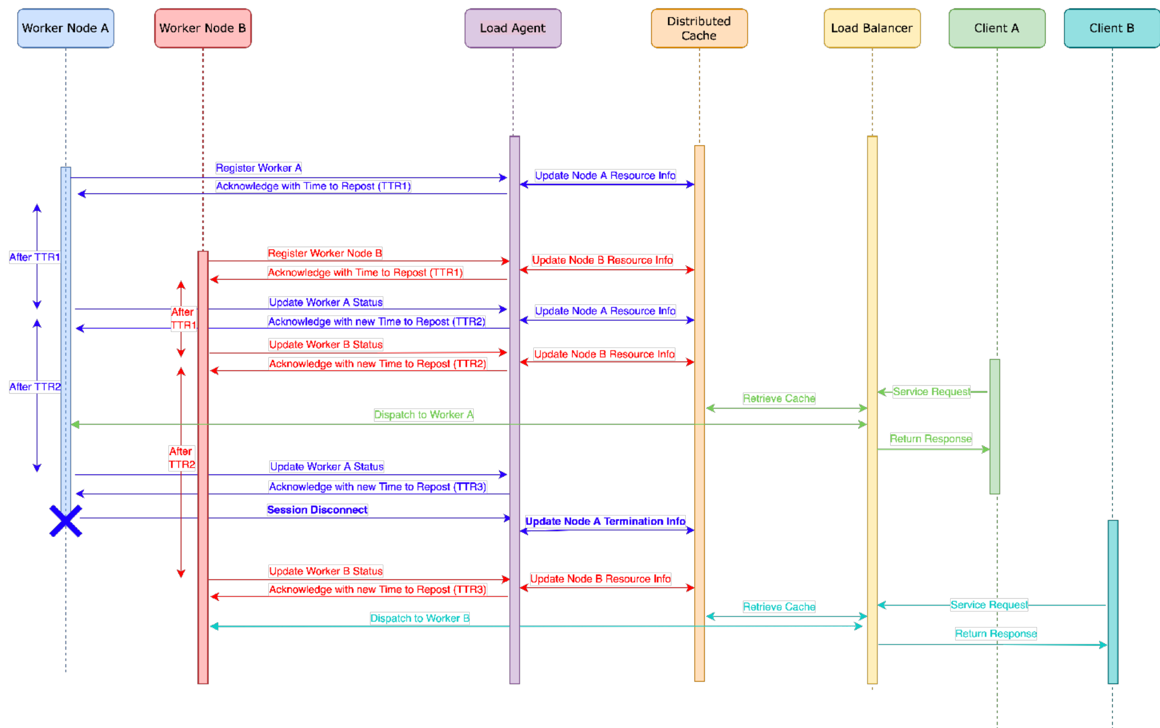

Fig. 4. Overall flow diagram to illustrate the fault event handling, recovery agent was not in scope

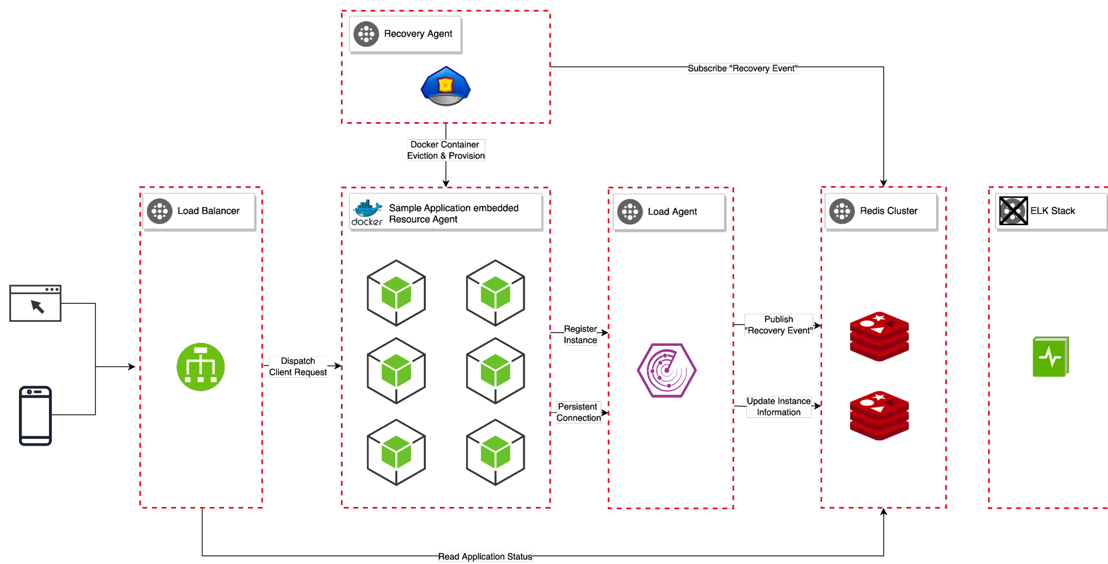

Fig. 5. Evaluation Implementation

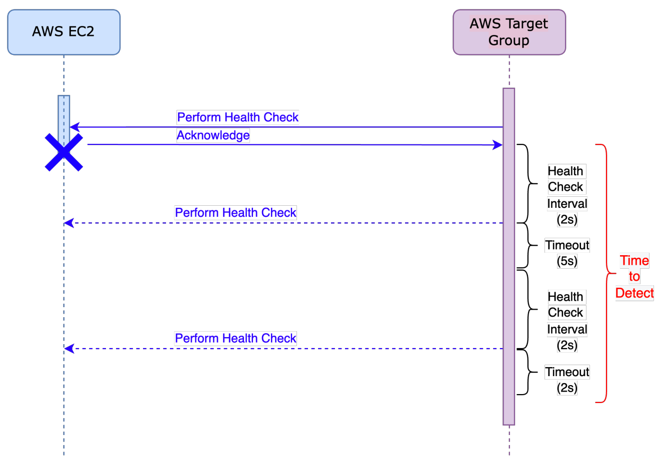

Fig. 6. AWS Load Balancer Worst Case scenario

We observed the number of fail counts was 3,990 when the kill-switch is 5 minutes, although this fail count is the highest amongst all scenarios, the downtime was only 7.343s so the overall SLA was 99.750%. When the kill switches increased to 10 minutes, the downtime became 0.023s so the overall Availability was 99.999% (five-ninth). This indicates that we can achieve "High Availability" even if our applications are scheduled to crash every 10 minutes. When the kill switch increased to 20 minutes, the SLA slightly dropped to 99.954%. All proposed scenarios have outperformed the AWS Application Load Balancer approach as shown in Table I.

In contrast, we have set up the AWS Application Load Balancer with the fastest fault recovery. Since the stress test is running on a remote environment, we created 10 threads that only triggered 10,000 requests individually, so the total execution was 100,000 requests. The total execution time for each iteration was around 35 minutes. As expected, we observed that the downtime decreased while the kill switch increased. The SLA was initially 95.93% when the kill switch was 5 minutes, then kept increasing to 96.72% and finally reached 98.06% when the kill switch was 20 minutes. The number of failed requests decreased by half from 2080 to 1021 during the 100,000 iterations.

VII. Conclusion

High availability has been one of the biggest challenges in application design. There are various techniques that can be used to improve the availability of a service which depends on various use cases. This research paper proposes to use a push-based mechanism with persistent connection in order to reduce the "Mean Time to Detect" such that the overall Service Level Agreement can be improved.

VIII. Acknowledgment

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