Realistic Error Injection for System Calls

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Abstract—In this paper, we present a novel fault injection framework called PHOEBE for reliability analysis with respect to system call invocation errors. First, PHOEBE enables developers to have full observability of system call invocations. Second, PHOEBE generates error models that are realistic in the sense that they resemble errors that naturally happen in production. With the generated error models, PHOEBE automatically conducts a series of experiments to systematically assess the reliability of applications with respect to system call invocation errors in production. We evaluate the effectiveness and runtime overhead of PHOEBE on two real-world applications in a production environment. The results show that PHOEBE successfully generates realistic error models and is able to detect important reliability weaknesses with respect to system call invocation errors. To our knowledge, this novel concept of “realistic error injection”, which consists of grounding fault injection on production errors, has never been studied before.

Index Terms—fault injection, error model, system call, chaos engineering

I. INTRODUCTION

In cloud-based software systems, one cannot fully control the production execution environment and many unexpected events keep happening: hardware issues, network fluctuations, and unanticipated user behavior \cite{29}. In order to assess and improve the reliability of software systems under such a changing and imperfect environment, different kinds of techniques are being researched, in particular fault injection \cite{36}. Fault injection evaluates software reliability by actively injecting errors into the software system under study \cite{32}. A recent trend in fault injection consists of injecting faults in production directly \cite{4}, \cite{8}, \cite{51}, this is known in the industry as “chaos engineering”. In this paper, we use “chaos engineering” as a timely and short term for referring to fault injection in production.

It is known that the space of all possible error injection is large \cite{5}. In other words, it is potentially intractable to explore all possible error scenarios. When doing fault injection in production, one does not want to impact users with unrealistic errors. In this paper, we address the problem of defining a tractable error injection space, by exclusively focusing on realistic errors. Our novel definition of realistic errors is that the injected errors resemble the ones that naturally happen in production. By injecting realistic errors, we identify reliability issues that are more relevant for developers.

In this paper, we realize this idea in the realm of system call errors. This focus is motivated by the essential role of system calls to analyze software behavior \cite{16}, and by the significant number of invocations to system calls that naturally fail in production. We propose a novel fault injection framework called PHOEBE, for doing realistic error injection at the system call level. To define realistic errors, PHOEBE first observes the natural system call invocation errors which happen in a production system. Then it analyzes those previously observed errors to synthesize a series of realistic error injection models that systematically amplify natural errors. The synthesis of those realistic injection models is the key novelty of PHOEBE. To sum, PHOEBE aims at bringing valuable insights into the error handling capabilities of an application with respect to realistic system call invocation errors.

We evaluate PHOEBE with two real-world applications: Hedwig, an email server that uses the SMTP and IMAP protocols, and TTorrent, a file downloading client based on the BitTorrent protocol. During the experiments in a production environment, PHOEBE observes that 84 million invocations to 23 unique system calls naturally fail. Based on these errors, PHOEBE synthesizes 32 and 33 realistic error injection models for HedWig and TTorrent respectively. The generated error models are then used to perform a series of chaos engineering experiments, which reveal important reliability shortcomings in both applications. The results of these experiments demonstrate the feasibility, applicability and added value of PHOEBE for analyzing reliability against system call invocation errors.

To sum up, our contributions are the following.

- Original insights about the presence of naturally happening system call errors in software systems.
- The concept of synthesizing realistic error injection models for system calls based on amplifying naturally happening errors observed in production.
- A fault injection framework called PHOEBE that implements the concept. PHOEBE takes as input the generated error models, conducts chaos engineering fault injection experiments, and outputs a reliability assessment with respect to system call invocation errors. The system is made publicly available for future research in this area at \url{https://bit.ly/repo-phoebe}.
- An empirical evaluation of PHOEBE on two real-world applications, an email server and a file downloading client, totaling 20.3K lines of code. The results show that PHOEBE is able to inject realistic errors at runtime, in production, with low overhead, in order to detect error handling weaknesses with respect to system call invocation errors.
The rest of the paper is organized as follows: Section II introduces the background. Section III shows that system call invocations do naturally fail. Section IV and Section V present the design and evaluation of PHOEBE. Section VI discusses the runtime overhead of PHOEBE and the threats to the validity of this research work. Section VII presents the related work, and Section VIII summarizes the paper.

II. BACKGROUND

A. Observability in Software Systems

A software system is said to be observable if it is possible to analyze the system’s internal state on the basis of its external behavior [33]. For example, by observing an HTTP 500 response code instead of 200, developers are able to know that there are some errors in the system when handling an HTTP request. In the context of errors, observability relates to the ability of detecting when an error naturally occurs in a software system. In this case, observability helps developers to evaluate the system’s error detection and handling capabilities.

There are mainly three categories of observability techniques [43]: 1) logging the system’s internal state. For example, using `Exception.printStackTrace()` method in Java to log stack information when an exception occurs. 2) monitoring metrics exposed by a system. For example, monitoring the memory usage of an application in order to detect memory leak issues. and 3) tracing externally observable events. For example, tracing an HTTP request that propagates through micro-services for timeout-related bug analysis.

B. Software Fault Injection

Software fault injection refers to a family of techniques for reliability evaluation [36]. By actively injecting errors into a software system, the error handling code in the system is triggered and its effectiveness can be evaluated. For example, memory errors can be injected to evaluate the reliability of an operating system with respect to memory errors [20]. Another example consists of injecting Java exceptions to evaluate the reliability of the try-catch blocks of a Java application [31].

An error injection model is a precise description of the injected errors, containing: 1) the kind of injected error, 2) how many and how frequently errors are injected, and 3) the time frame when errors are injecting.

Chaos engineering is a recent fault injection technique, which injects faults in production in order to improve a system’s reliability [8]. Chaos engineering has been extensively studied with respect to fault injection related to the environment: server crashes [2], disk issues [34] and network fluctuations [12]. In chaos engineering, the injected faults are called “perturbations” or “turbulence”. In order to verify a software system’s ability to resist these perturbations, chaos engineering actively injects errors into the production system and observe the visible effects on the system [5].

C. System Calls

System call is a fundamental interface between an application and the kernel [46]. In modern operating systems, critical resources such as hardware devices and process scheduling are usually managed by the kernel. When a user application needs to interact with a given critical resource, the corresponding system call is invoked. For example, in Linux, the `open` system call is invoked when an application needs to open or create a file. Linux defines and implements more than 300 unique system calls, as well as over 100 error codes to precisely report on errors upon invocation of those system calls [45].

As discussed in Section II-B, an application may be perturbed by both hardware errors and software errors. Sometimes such errors can not be handled by the operating system on its own. Thus it propagates the error to the application, by failing a system call invocation with an error code. System call invocation errors do happen naturally, which will be further explained in the following section.

III. Natural System Call Invocation Errors

Due to the complexity of execution environments in production, there are always unanticipated errors in a software system [8], [12]. For instance, it is known that servers do regularly crash in production [10]. In this paper, we focus on system call errors, which is a topic that has been little studied. In this section, we present original empirical observations that show that system call invocation errors naturally happen oftentimes.

A. Methodology

We use the mature and well-known Java-based web server Apache Tomcat 9 as the experiment target. After deploying Tomcat into a production-like environment, we simulate 10 users who keep sending requests concurrently to the server for 1 minute. During this execution, a system call monitor is attached to Tomcat to capture all system call invocations. The monitor records both the system call and its return code. At last, we analyze this monitored information to see if there are any system call invocation errors naturally happening.

B. Magnitude of System Call Invocation Errors in the Wild

During the experiment, there are a total of 700,000 requests sent to the Tomcat server in one minute. All of them are responded with a 200 HTTP status code (success) and the corresponding web page is well sent. Global observations about system call invocations are as follow: there are 20 unique system calls, and a total of 18.4 million invocations. Most interestingly for us, there 85.4K system call invocation errors. Despite that 0.46% of system call invocations return an error code, Tomcat still successfully fulfills all the HTTP requests, thanks to its error-handling code.

Table I provides some detailed insights about those errors. During sending the requests to Tomcat, 5/20 system calls failed at least once. Each row in the table describes one system call invocation error, including its error code, the number of errors, the number of total invocations of this system call, and the percentage of errors. Let’s take the third row as an example. `futex` is typically used as a blocking construct in the context of shared-memory synchronization. During the experiment,
1.73K out of 2.78M (0.062%) futex invocations fail with an error code ETIMEDOUT. The error code ETIMEDOUT means that the invocation employs a timeout specified as an argument, and the timeout expires before the operation is completed \[47\]. This indicates that despite the timeout of the operation, there is no critical or even visible impact on the application.

To sum up, we have shown that system call invocation errors naturally happen, even for a usage scenario as simple as requesting a file via HTTP. Those errors are handled somewhere in the software stack, either in a library, in the JVM, or in the code of Tomcat, yet no error or degradation is observed in the application. Those errors are actively injected in production according to a given error rate. If the application’s behavior is acceptable under fault injection, the developers gain confidence in the application’s error handling capabilities. Otherwise, with the help of PHOEBE, developers learn more about how the application behaves when system calls fail, and can fix the uncovered reliability issues.

### B. Definitions

#### a) System Call Invocation Error: An invocation of a system call is deemed an error if it returns an error code \[46\]. These error codes are systemically specified and documented in the operating system under consideration, Linux in our case. In Linux, the error codes are negative values defined in a header file named \texttt{errno.h} \[45\]. In this paper, an invocation to a given system call \texttt{syscall} yielding a given error code \texttt{E} is denoted by \texttt{syscall:E}.

#### b) Monitoring Interval: A monitoring interval is a period of time along which metrics of interest are collected. The length \( t \) of a monitoring interval in seconds means that PHOEBE collects metrics over \( t \) seconds, and reports them to an external component such as a time-series database every \( t \) seconds. The smaller \( t \) is, the more frequently the monitor reports the metrics.

#### c) Error Rate: An error rate \( r \) of a system call invocation error \( s:e \) during the length of monitoring interval \( i \) is denoted as \( r(s,e,i) \). The value of \( r(s,e,i) \) is calculated as

\[
  r(s,e,i) = \frac{\text{number of errors}(s,e,i)}{\text{total number of invocations}(s,i)}
\]

where \( \text{number of errors}(s,e,i) \) means the total number of errors \( s:e \) in \( i \). \( \text{total number of invocations}(s,i) \) records the total number of invocations of system call \( s \) made in \( i \) no matter what a return code is.

#### d) Realistic Error Injection Model: In this paper, an error injection model is a triple \((s,e,r)\) that states what invocation error \( s:e \) is injected, with an error rate of \( r \). An error model is considered as realistic if the error \( s:e \) is naturally observed in a production-like running environment.

#### e) Behavioral Assessment Criteria (BAC): The normal behavior of a software system consists of functionalities that can be successfully executed by users \[16\]. In this paper, we define the “Behavioral Assessment Criteria” as a set of application-specific metrics that capture the normal behavior and potential deviations from the perspective of users. The series of metric values observed in the absence of perturbations forms the normal behavior. The longer we observe these metrics, the more accurately the normality of the behavior is assessed. An application’s normal behavior is often described at the application level, with application specific metrics: for instance, Netflix uses metric SPS – stream starts per second – as their major metric for capturing the normal behavior of their video streaming system \[6\].

#### f) Chaos Engineering Experiment: In this paper, a “chaos engineering experiment” is a consecutive sequence of monitoring intervals during which system call invocation errors are actively injected in production according to a given

### IV. DESIGN & IMPLEMENTATION OF PHOEBE

#### A. Working Example

As discussed in \[Section III\] system call invocation errors indeed happen in production. Although system call invocation errors naturally occur, it may take a long time to observe a specific type of rare error. Similarly, the observed behavior may not be sufficient to analyze reliability against these natural errors.

In order to bring more insights about how an application behaves when a system call invocation error occurs, PHOEBE follows the principles of chaos engineering to actively inject system call invocation errors into an application running in production.

First of all, PHOEBE provides observability on system calls. It collects system call invocations including their name, execution time and return code, with low overhead. By achieving the full observability at the system call level, PHOEBE enables analysis of natural system call invocation errors.

Secondly, PHOEBE captures rare system call invocation errors and makes them happen more frequently. This can be considered as chaos engineering for system calls (per the definition of \[Section II-B\]). PHOEBE provides the developers with information about the behavior of the system under system call perturbations. If the application’s behavior is acceptable under fault injection, the developers gain confidence in the application’s error handling capabilities. Otherwise, with the help of PHOEBE, developers learn more about how the application behaves when system calls fail, and can fix the uncovered reliability issues.
error injection model. The goal of a chaos engineering experiment is to analyze to which extent the injected errors make the system deviate from its behavioral assessment criteria in production.

C. Architecture of PHOEBE

Figure 1 shows the architecture of PHOEBE, there are six components in PHOEBE: 1) natural error monitor (see Section IV-D1), 2) application behavior monitor (see Section IV-D2), 3) realistic error injection model synthesizer (see Section IV-D3), 4) system call invocation error injector (see Section IV-D4), 5) experiment orchestrator (see Section IV-D5) and 6) metrics visualizer (see Section IV-D6).

Briefly, those components work as follows. The natural error monitor collects and reports system call related metrics, those metrics are inputs for the error injection model synthesizer. The synthesizer analyzes the natural system call errors and computes a realistic error injection model. The system call invocation error injector takes an error model as input, and conducts a set of chaos engineering experiments on the application. The experiment flow is automated by the experiment orchestrator. Finally, the metric visualizer provides a live dashboard for the developer to display the monitoring information.

D. Component Design

1) Natural Error Monitoring: The natural error monitor captures metrics related to system calls. Given a monitoring interval length $t$, the monitor regularly captures a set of metrics including 1) the name and amount of different system call invocations during $t$, 2) the return code $e$ of system call invocations, 3) the execution time $l$ of each system call and 4) the error rate $r$ if a specific system call invocation fails.

Per our definition of a monitoring interval in Section IV-B, the choice of a length $t$ for the monitoring interval results from an engineering trade-off. A smaller $t$ gives a more accurate description of metric changes thanks to a more frequent sampling. However, this brings more monitoring overhead with respect to performance and storage. For example, a small interval (e.g., 1 second) makes the monitor report metrics very frequently: lots of monitoring data is generated, which requires significant calculation and storage resources. Meanwhile, a large interval length (e.g., 1800 seconds) leads to more sparse monitoring data, which gives less accurate information about errors. Per our pilot experiment, $t = 15$ seconds is a good trade-off between overhead and precision, this is PHOEBE’s default monitoring interval length.

2) Application Behavior Monitoring: PHOEBE collects a set of behavioral assessment criteria to model the application behavior. The criteria combine general metrics, language-specific metrics and application-specific monitoring metrics which capture the normal behavior: 1) general metrics: PHOEBE captures OS-level metrics such as CPU load 2) runtime-specific: PHOEBE has dedicated support for Java and captures heap memory usage, garbage collection time 3) application-specific metrics: PHOEBE can capture HTTP requests for certain Java libraries. The developers can define more behavior monitoring, for example, the ratio of successful database requests per second can be considered as a metric for an enterprise applications.

Both language-specific and application-specific behavior monitoring requires observability features that are specific to an execution environment. In particular, they require code instrumentation. The current prototype implementation of PHOEBE supports software systems that are running on a Java Virtual Machine with support for JVM metrics and bytecode instrumentation.

3) Realistic Error Model Synthesis: There are many different error codes for each system call. In principle, it is possible to inject all possible error codes for all system calls. However, this is very time consuming, and some combinations never happen in the real world. In order to increase the efficiency and relevance of chaos engineering experiments, the error model synthesizer focuses on errors that occur naturally. It takes the observed natural errors as input, and generates a set of realistic error injection models for chaos engineering experiments.

Recall that an error injection model is a triple $(s, e, r)$, in which $s$ stands for the system call, $e$ means the error code of a system call invocation, and $r$ is the error rate. Given an observed system call $s$ that failed with error code $e$, the synthesizer keeps $s$ and $e$, and generates different rate values by applying an error rate amplification algorithm which is described in Algorithm 1. For each system call invocation error, we consider four different cases:

- **Case 1: sporadic errors** (condition at line 5) The natural error rate is very low: this means that it takes a very long time to observe such an error naturally. In this case, the synthesized error injection model uses a fixed error rate, large enough to inject the error during the experiment, with high probability.

- For example, if the natural error rate for system call $S$ with error code $E$ is $0.000001$, this error is difficult to be observed in a normal running environment. Thus the synthesizer amplifies it to a fixed value, e.g., $0.5$ (configurable by the developer). This means that during a fault injection experiment, an invocation of system call $S$ has a 50% possibility to be failed with error code $E$.

- **Case 2: fluctuating errors** (condition at line 9) PHOEBE observes a big difference between the maximum and minimum error rate over different monitoring intervals. In this case, the synthesizer sets the rate of the model to the maximum error rate.

- For example, system call $S$ fails with error code $E$ several times during a consecutive sequence of monitoring intervals. The minimum error rate in a monitoring interval is $0.01$ and the error rate in another interval is $0.5$. This means that system call $S$ sometimes fails once for every 100 invocations or for half of such system call invocations. The synthesizer sets the error rate to $0.5$ in the model. During a chaos engineering experiment, invocations to this $S$ always have the highest possibility of error.

- **Case 3: steady errors** (“else” statement at line 11) The maximum and minimum error rate over a consecutive se-
sequence of monitoring intervals are close to each other, and the rate is higher than a threshold. This means that an error happens often, can be easily observed and can be easily injected. In this case, the synthesizer multiplies the maximum original error rate by a fixed amplification factor $1 < f < 2$. For example, an amplification rate $f = 1.2$ means that there are 20% more such errors compared to what happens naturally.

**Case 4: worst case** (statement at line 16) for all system call invocation errors, PHOEBE also generates a worst-case error injection model: for every observed error type, one model is generated with maximal of 100% error injection model: for every observed error type, one model is generated with maximal of 100% error injection model: for every observed error type, one model is generated with maximal of 100% of all invocations to that system call fail). This lets developers see how an application behaves in a catastrophic scenario.

Note that in PHOEBE, the minimum, mean and maximum error rates are calculated from a consecutive sequence of monitoring intervals. Considering there may be extreme cases in production that make the minimum and maximum values deviate a lot from the others, the Algorithm 1 takes the 5th percentile and 95th percentile respectively as the minimum and maximum error rate.

4) **System Call Invocation Error Injection**: In order to trigger a specific system call invocation error, the error injector in PHOEBE instruments the system call invocations. The concrete workflow includes: 1) registering the injector to the target system call’s return event, 2) calculating the injection conditions before the target system call invocation returns, and 3) overriding the system call return value if all the conditions have been met. The system call invocation error injector supports the following triggering conditions: Process id and process name. The injector focuses on an application’s process.

When the injector is registered to a system call exit event, the injector uses the process id or the process name to select all system call invocations of that process. Error rate. The injector triggers an error according to the error rate specified in an error injection model. Before a target system call returns, the injector generates a random number $p (0 < p \leq 1)$ and compares it with the error rate $r$. This condition holds when $p$ is less than or equal to $r$. Total number of errors. The injector injects an error within a specific absolute amount of system call invocation errors. Successful calls only. The injector only injects errors on invocations that are initially successful. Natural system call errors are untouched and their return code remains the same.

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**Algorithm 1** Realistic Error Injection Model Synthesis

**Input:**
- System call monitoring metrics in a consecutive sequence of monitoring intervals $L$;
- An upper boundary for using fixed error rate $b$;
- A vector that contains fixed error rates for rare system calls $v$;
- Amplification factor $f$;

**Output:**
- A list of error injection models $F$;
1. $L' \leftarrow$ Categorize $L$ by system call $s$ and return code $e$;
2. $L' \leftarrow$ Calculate the minimum (5th percentile), mean and maximum (95th percentile) value per monitoring interval of each $(s, e)$’s error rate;
3. $F \leftarrow \emptyset$
4. for each system call invocation error $(s, e, r) \in L'$ do
5. \hspace{1em} if $r_{\text{max}} < b$ then
6. \hspace{2em} for each fixed error rate $r \in v$ do
7. \hspace{3em} $F \leftarrow F \cup \text{generateErrorModel}(s, e, r)$;
8. \hspace{2em} end for
9. \hspace{1em} else if $r_{\text{max}}/r_{\text{min}} > 10$ then
10. \hspace{2em} $F \leftarrow F \cup \text{generateErrorModel}(s, e, r_{\text{max}})$;
11. \hspace{1em} else
12. \hspace{2em} if $r_{\text{max}} \cdot f < 1$ then
13. \hspace{3em} $F \leftarrow F \cup \text{generateErrorModel}(s, e, r_{\text{max}} \cdot f)$;
14. \hspace{2em} end if
15. \hspace{2em} end if
16. \hspace{1em} $F \leftarrow F \cup \text{generateErrorModel}(s, e, 1)$;
17. \hspace{1em} end for
18. return $L'$;
5) **Orchestration**: The experiment orchestrator in PHOEBE is designed to conduct fault injection experiments in a fully automatic manner. The orchestrator takes an experiment configuration file format as input. The configuration file contains a set of experiments, each specified by a duration and an error injection model as defined in Section IV-B. For each experiment, the orchestrator attaches the error injector with its error model, capturing the application’s behavior with the help of the application behavior monitor, and comparing the behavior under fault injection according to the behavioral assessment criteria. When the experiment duration has passed, the orchestrator turns off the injector and outputs the experiment result.

6) **Visualization**: In order to fetch and analyze the monitoring information, developers are given a metric visualization dashboard. This dashboard displays metrics in line charts so that it is convenient to investigate the change of different system call invocations. These line charts include every system call’s error rate and the number of invocations over time. For other metrics such as the number of system call invocations, developers can also directly make queries to the monitoring database via the dashboard.

**E. Implementation**

PHOEBE captures and overrides system calls with the BPF Linux Kernel module. PHOEBE’s BPF programs are loaded with BCC. PHOEBE’s monitoring infrastructure and system call invocation error injector are implemented in Python. All the monitoring metrics are saved into Prometheus, a time series database. The visualization component is supported by Grafana, an open source visualization platform. For the sake of open research, the source code and experiment results of PHOEBE are publicly available at [https://bit.ly/repo-phoebe](https://bit.ly/repo-phoebe)

**V. EVALUATION**

This section discusses the evaluation of PHOEBE, which focuses on what reliability problems can be detected by injecting system call invocation errors using a realistic error model.

**A. Subject Programs**

In order to evaluate PHOEBE, a set of representative programs needs to be selected. The selection criteria are based on: 1) the program is a real-world project that has users (it is neither a research prototype nor specifically implemented for this evaluation), 2) the program is medium-sized so that it can be deployed using the computing resources that are available in the research lab, 3) there is a production workload or equivalent that can be used for the chaos engineering experiments, 4) the subject must be monitorable with PHOEBE’s behavioral monitoring component for Java (see Section IV-D2). Based on those systematic criteria, we select 2 projects for the experiments: 1) HedWig, an email server written in Java; 2) TTorrent, a client for downloading files using the BitTorrent protocol, implemented in Java.

**B. Experiment Protocol**

For both case studies, we follow a 4-step protocol, described below. In the following subsections, we go into the details of how we specialize these steps, according to the application-specific production-like workload and the behavioral assessment criteria for each subject program, in order to trigger different execution paths in the program.

First, we build a realistic error injection model by observing natural system call errors (per our definition in Section IV-B). To this end, PHOEBE’s monitor component is attached to the program to collect system call related metrics without any error injection.

Secondly, PHOEBE’s error injection model synthesizer takes the monitored system call information as input. It generates a set of error injection models for chaos engineering experiment.

Thirdly, the behavioral assessment criteria of the program is set up based on the monitoring metrics. The experiment orchestrator conducts error injection experiments defined in Section IV-B on the program according to the generated error injection models.

At last, the program behavior under error injection is evaluated using the behavioral assessment criteria. A report is generated to show different impacts each error injection has on the program.

**C. Experiment on HedWig**

1) **Experiment Specificities for HedWig**: We use version 0.7 of HedWig for the experiments. We collect a real workload for our experiments, as follows: we create an email account, to receive emails from real-world mailing lists; we let the email server run for 90 days. As a result, 351 emails with different headers and bodies are collected. These emails and the observed server behavior form the experimental dataset.

In order to define the behavioral assessment criteria of HedWig server, we deploy a domain specific health checker. It executes the following workflow: 1) the checker logs into the server using one test account, 2) the checker randomly picks up an email from the dataset, and forwards it to another test account hosted on the server, 3) the checker logs into the server again using the latter account and tries to fetch the latest email, and 4) the checker compares the fetched email with the original sent email to test if the email is correctly delivered. After running the health checker for 24 hours, we collect the following behavioral assessment criteria: the percentages of success (SU), sending errors (SF), fetching errors (FF), validation errors (VF), and server crashes (SC).

Considering that the HedWig server may not be able to correctly deliver emails even after error injection has stopped, we collect an additional Boolean metric called state corruption (CO) during the experiments. The CO metric is calculated by a post inspection step for each experiment: after the error injector is turned off, a randomly selected email is sent, fetched, and validated as usual to test if the server is back to working normally. If the post inspection fails, CO is true.
In this case the server needs to be restarted before conducting other experiments.

2) Experimental Results: Table II lists the natural errors observed by PHOEBE’s monitor over a period of 24 hours, or 5760 monitoring intervals of 15 seconds. Each row in the table describes how many invocations (count) to a given system call yielded a given error code. The minimum (5th percentile) and maximum (95th percentile) error rates, encountered in those 5760 monitoring intervals are also reported, as well as the mean error rates, averaged over those intervals. The data in this table is one of the inputs (system call monitoring metrics \( L \)) for Algorithm I. The last column reports on how our algorithm categorizes each entry in the table (Section IV-D3).

For example, the second row of the table shows that the error type connect:ENOENT occurred 151 times during the 24 hours under monitoring. The minimum error rate encountered in a 15 seconds monitoring interval for that specific error was 0.090909, the maximum rate was 1. The mean error rate was 0.237583. In this case, there is a large gap between the minimum rate and the maximum rate, which indicates that in some monitoring intervals HedWig invokes connect system calls and most of them are successful. While in other monitoring intervals, the percentage of failed connect system calls with ENOENT is higher. Thus this case meets the conditions of case 3 in Section IV-D3.

Table II also shows different patterns of natural system call invocation errors. Some natural errors rarely happen in 24 hours, such as mkdir with ENOENT which only fails once. While some natural errors are frequent, for example futex with ETIMEDOUT.

We build the behavioral assessment criteria of Hedwig as follows. The health checker tries to send 3824 randomly selected emails from one account to another. We observe the following metrics: 3821 out of 3824 emails are successfully sent, fetched and validated; all the 3824 emails are successfully sent. SU=100% and SF=0%; 1 fetching error is reported, FF=0.026%; 2 validation errors are reported, VF=0.052%; there is no server crash reported, SC=0%. These metrics form the behavioral assessment criteria that we use for a comparison during each chaos engineering experiment.

Next, we synthesize realistic error models. The inputs for Algorithm I are, the system call monitoring metrics \( L = \) Table III upper boundary error rate \( b = 0.3 \), a vector of fixed error rates \( (0.5, 0.75) \) and amplification factor \( f = 1.5 \). The algorithm synthesizes 32 error models for chaos engineering experiments. Table III describes 24 error models together with their experimental results. We omit 8 error models for which PHOEBE did not inject any errors during the experiments. The potential reason is production workload during the experiments does not invoke these system calls.

Table III is the main outcome of the chaos engineering experiments on Hedwig. For example, the first row of Table III is a realistic error injection model based on the natural invocation error accept:EAGAIN (row 1 in Table II) which meets case 3 in Section IV-D3. During the experiment with error rate 0.75, PHOEBE injects 27 errors in total into the system calls, in addition to the natural ones. 18.8% of emails were successfully sent, fetched and verified. However, these errors caused sending errors for 56.2% of emails and fetching errors for 25% of emails. There was no validation error or server crash detected. The post inspection for this experiment passed, which means the injected errors do not impact the server after the injection has been stopped. Considering the behavioral assessment criteria of Hedwig mentioned above, failing invocations to accept do cause a negative impact on Hedwig’s functionalities.

The results of these chaos engineering experiments bring insights about how HedWig server behaves under different
operating system perturbations. Based on the impact of a system call invocation error on Hedwig, the experiment results are categorized into three types: 1) an injected system call invocation error does not violate any behavior assessment criterion, is marked as "√", in the table, 2) an injected error has an impact on the functionality only during error injection (SF, FF, and VF related violations), this is marked as "■", and 3) an injected error causes severe side effects like server crash (SC) or server state corruption (CO), this is marked as "●". For example, futex related errors may lead the server to crash. Failing invocations to read, recvfrom and sendto can corrupt the application’s running state and have a long-existing impact after an error happens. These categories of system call invocation errors are helpful to guide developers to design specific error handling mechanisms with respect to system call invocation errors.

D. Experiment on T Torrent

1) Experiment Specificities for T Torrent: We use version 2.0 of T Torrent for the experiments. As T Torrent uses BitTorrent protocol to download files from the Internet, its workload during file downloading can be considered as a production-like workload. To make the workload more various, T Torrent randomly downloads ubuntu-18.04.4, ubuntu-19.10, or ubuntu-20.04 using different torrent files for each experiment. According to the network condition and the experiment virtual machine’s power, the average time of downloading one of the iso files in the data set is about 30 seconds. For each experiment, the orchestrator adds a 150 seconds time out for the T Torrent process. If T Torrent is still running but the file is not downloaded after 150 seconds, the orchestrator kills the T Torrent process and begins the next round of download.

We run T Torrent to randomly download different Ubuntu distributions for 24 hours without injecting errors, to determine its behavioral assessment criteria and observe the natural occurrences of system call invocation errors. Our key metric for the behavioral assessment criteria is the percentage of executions that successfully download files. When system call invocation errors are injected, T Torrent might behave in the following ways: 1) SU (success): T Torrent successfully downloads the target file, with a correct md5 checksum. This means T Torrent still meets the behavioral assessment criteria when the errors are injected. 2) VF (validation error): T Torrent downloads the file, but the file’s checksum is incorrect. This means a data corruption happens during the downloading process. 3) ST (stalled) T Torrent fails to download the file in a limited time, which is considered as stalled. The experiment orchestrator kills the T Torrent process and starts another round of experiment. 4) CR (crash): T Torrent directly crashes when an error is injected.

Since T Torrent is a client-side application, each chaos engineering experiment with T Torrent initializes a new process. There is no need to add post inspections for each experiment.

2) Experimental Results: A 24-hour (563 rounds) run of T Torrent to download different versions of Ubuntu distributions, shows that 547 out of 563 executions successfully download the target file with a correct MD5 checksum, SU=97.2%. The other 16 executions all lead to a stalled state, ST=2.8%. There is no validation error or crash detected, VF=CR=0%. PHOEBE’s natural error monitor collects 17 different system calls that naturally fail. They are summarized in Table IV. Each row in the table records one system call invocation error, including its system call name, error code, the total number of errors, the minimum (5th percentile), mean, maximum (95th percentile) value of the error rate per monitoring interval (15 seconds), and its corresponding cases for error model synthesis described in Section IV-D3.

For example, we observe 3.67K access system call invocation errors with an error code ENOENT, over the 563 rounds of execution. The minimum, mean and maximum error rate per monitoring interval are respectively 0.549091, 0.574295 and 0.66667. This indicates that in some monitoring intervals, 55% of the invocations to access fail with ENOENT. In some other monitoring intervals, more than 66% of the invocations to access fail with such an error code.

PHOEBE synthesizes 33 realistic error injection models for chaos engineering experiments. The upper boundary error rate b = 0.3, the vector of fixed error rates is (0.5, 0.75) and the amplification factor f = 1.5. The generated error models and the corresponding experiment results are presented in Table V. Similar to Table III, the rows where the injection count is zero are omitted as well. The experiment results are categorized into 3 types: 1) T Torrent successfully downloads the file with a correct checksum under error injection (SU), which is marked as "√" in the table, 2) T Torrent gets stalled when an error is injected (ST), which is marked as "■", 3) T Torrent reports the file is downloaded but the checksum of the file is incorrect (VF), or T Torrent immediately crashes after injecting an error (CR), which is marked as "●".

PHOEBE was able to highlight the fact that T Torrent has different levels of reliability against different system call invocation errors. For example, T Torrent is fully resilient against errors of types epoll_ctl:ENOENT, epoll_wait:EINTR

### Table IV: The Observed Natural Errors of T Torrent When Downloading a Ubuntu Distribution ISO File

| Syscall and Error Code | Count | Error Rate (min, mean, max) per 15 sec period | Case |
|------------------------|-------|---------------------------------------------|------|
| access:ENOENT          | 3.67K | 0.549091, 0.574295, 0.666667                | 3.4  |
| connect:EPINPROGRESS   | 13.5K | 0.500000, 0.917268, 1.000000                 | 3.4  |
| connect:ENOENT         | 1.05K | 0.070175, 0.553490, 1.000000                 | 2.4  |
| epoll_ctl:ENOENT       | 6.88K | 0.000030, 0.189846, 1.000000                 | 2.4  |
| epoll_wait:EINVAL      | 79    | 0.333333, 0.753165, 1.000000                 | 3.4  |
| futex:EAGAIN           | 182K  | 0.001515, 0.088186, 0.177777                 | 1.4  |
| futex:ETIMEOUT         | 660K  | 0.004235, 0.384304, 0.500000                 | 2.4  |
| getsockopt:ENO.SOCK    | 262   | 0.009064, 0.178715, 0.333333                 | 2.4  |
| lstat:ENOENT           | 786   | 0.024390, 0.052329, 0.052862                 | 1.4  |
| mkdir:EXIST            | 262   | 1.000000, 1.000000, 1.000000                 | 3.4  |
| openat:ENOENT          | 13.1K | 0.135187, 0.234193, 0.342857                 | 3.4  |
| read:EINVAL            | 478   | 0.000007, 0.000034, 0.000097                 | 1.4  |
| read:ECONNRESET        | 763   | 0.000007, 0.036329, 0.125000                 | 1.4  |
| stat:ENOENT            | 17.0K | 0.114286, 0.387320, 0.571429                 | 3.4  |
| unlink:ENOENT          | 362   | 0.666667, 0.685808, 0.666667                 | 3.4  |
| write:ECONNRESET       | 58    | 0.000016, 0.000719, 0.001954                 | 1.4  |
| write:EPipe            | 6     | 0.000017, 0.000023, 0.000031                 | 1.4  |
TABLE V
CHAOS ENGINEERING EXPERIMENT RESULTS ON T Torrent

| Target & Error  | F. Rate | Inj. | Behavioral Assessment Criteria   | Normal Run | Monitor On | Overh. |
|-----------------|---------|------|----------------------------------|------------|------------|--------|
| access:ENO.     | 1.0     | 119  | SU:0, VF:0, ST:0, CR:100%        |            |            |        |
| connect:Ein.    | 1.0     | 144  | SU:0, VF:0, ST:100%, CR:0        |            |            |        |
| connect:ENO.    | 1.0     | 144  | SU:0, VF:0, ST:100%, CR:0        |            |            |        |
| epoll_ctl:ENO.  | 1.0     | 1.21MB | SU:100%, VF:0, ST:0, CR:0      |            |            |        |
| epoll_wait:ENTR.| 1.0     | 22.1MB | SU:100%, VF:0, ST:0, CR:0      |            |            |        |
| futex:EAG.      | 0.5     | 178  | SU:13.5%, VF:0, ST:0, CR:86.5%  |            |            |        |
| futex:EAG.      | 0.75    | 234  | SU:0, VF:0, ST:0, CR:100%       |            |            |        |
| futex:ETI.      | 1.0     | 399  | SU:0, VF:0, ST:0, CR:100%       |            |            |        |
| futex:ETI.      | 0.5     | 286  | SU:0, VF:0, ST:0, CR:100%       |            |            |        |
| getline:ENO.    | 0.333   | 152  | SU:62.5%, VF:0, ST:37.5%, CR:0  |            |            |        |
| getline:ENO.    | 1.0     | 4    | SU:0, VF:0, ST:0, CR:100%       |            |            |        |
| openat:ENO.     | 0.514   | 243  | SU:0, VF:0, ST:100%, CR:0       |            |            |        |
| openat:ENO.     | 1.0     | 238  | SU:0, VF:0, ST:100%, CR:0       |            |            |        |
| read:EAG.       | 0.5     | 120  | SU:0, VF:0, ST:100%, CR:0       |            |            |        |
| read:EAG.       | 0.75    | 119  | SU:0, VF:0, ST:100%, CR:0       |            |            |        |
| read:EAG.       | 1.0     | 119  | SU:0, VF:0, ST:100%, CR:0       |            |            |        |
| read:ECO.       | 0.5     | 119  | SU:0, VF:0, ST:100%, CR:0       |            |            |        |
| read:ECO.       | 0.75    | 119  | SU:0, VF:0, ST:100%, CR:0       |            |            |        |
| read:ECO.       | 1.0     | 119  | SU:0, VF:0, ST:100%, CR:0       |            |            |        |
| unlink:ENO.     | 1.0     | 20   | SU:0, VF:0, ST:0, CR:0          |            |            |        |
| write:ECO.      | 0.5     | 84   | SU:0, VF:0, ST:100%, CR:0       |            |            |        |
| write:ECO.      | 0.75    | 127  | SU:0, VF:0, ST:100%, CR:0       |            |            |        |
| write:ECO.      | 1.0     | 184  | SU:0, VF:0, ST:100%, CR:0       |            |            |        |
| write:EI.       | 0.5     | 858  | SU:0, VF:0, ST:100%, CR:0       |            |            |        |
| write:EI.       | 0.75    | 138  | SU:0, VF:0, ST:100%, CR:0       |            |            |        |
| write:EI.       | 1.0     | 184  | SU:0, VF:0, ST:100%, CR:0       |            |            |        |

Table VI shows the runtime overhead of PHOEBE’s natural error monitor on HedWig and T Torrent. For example, the first group of rows in the table shows the 5 metrics captured for HedWig: 1) the heap memory usage, 2) the CPU load, 3) the memory usage per database transaction, 4) the CPU time per transaction and 5) the JDBC query time on average. These 5 metrics respectively increase by 5.0%, 5.9%, 0.4%, 7.4%, and 8.0% with system call monitoring, which is considered as acceptable. The same conclusion applies to T Torrent, where the maximum overhead is 4.9%.

As a summary, the runtime overhead cost by PHOEBE is comparable to other monitoring tools for production usage like Glowroot [17] and SWAT [21].

B. Threats to Validity

A critical bug in PHOEBE that impacts the trustfulness of our measurements would impact internal validity. Since our code is open-source, future work and researchers in this domain are able to verify it.

The behavior assessment criteria are essential for analyzing the application behavior under fault injection. If we have missed an application-specific behavior assessment criterion, this would impact construct validity. However, we are confident that this is not the case since we understand the domain of email communication and file downloading.

Finally, PHOEBE focuses on applications running on top of the Java Virtual Machine because application behavior monitoring requires language- and technology-specific features. We notice that the JVM itself may 1) either create natural system call errors 2) or remediate some errors directly (i.e. we are not observing the effectiveness of application-specific reliability). Future work may explore the interplay between the JVM and the application error-handling mechanisms with respect to system call invocation errors.

VI. DISCUSSION

A. Runtime Overhead of PHOEBE

1) Experiment Protocol: Monitoring and injecting system call invocation errors may impact application performance. We now measure and discuss the runtime overhead of PHOEBE. Firstly, we keep an application running in production for a certain amount of time without PHOEBE attached, and we record performance-related metrics. Secondly, the application is executed for the same duration with PHOEBE’s monitor attached. The same performance metrics are captured. Finally, the performance difference is analyzed to determine if PHOEBE has an acceptable runtime overhead.

We collect both generic and application-specific performance metrics. The generic metrics are: 1) heap memory usage in the JVM collected with Glowroot, 2) CPU load. Since HedWig depends on a MySQL database, the JDBC transactions are also picked up as an application-specific performance metric. For T Torrent, we measure the average download time.

2) Runtime Overhead Evaluation Results: Table VI shows the runtime overhead of PHOEBE’s natural error monitor on HedWig and T Torrent. For example, the first group of rows in the table shows the 5 metrics captured for HedWig: 1) the heap memory usage, 2) the CPU load, 3) the memory usage per database transaction, 4) the CPU time per transaction and 5) the JDBC query time on average. These 5 metrics respectively increase by 5.0%, 5.9%, 0.4%, 7.4%, and 8.0% with system call monitoring, which is considered as acceptable. The same conclusion applies to T Torrent, where the maximum overhead is 4.9%.

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VII. RELATED WORK

In this section, we discuss work related to fault injection and observability.

A. Fault Injection

Fault injection techniques aim at evaluating the error handling mechanisms of a software system [36], [42], [52]. fault and unlink:ENOENT, as shown in rows 4, 5 and 21. In other words, those errors had no negative impact on the behavior assessment criteria for T Torrent, which was still able to download the file under such error injection. However, T Torrent is particularly sensitive to invocation errors related to access, futex, openat and read, making T Torrent to crash instantly. Other types of errors, related to connect, gethostname and write resulted in T Torrent stalling and need further investigations to determine if T Torrent can eventually recover.
injection research has heavily focused on hardware errors [26], [32]. Another line of research work concerns the injection of high-level software faults [25], [28], [48].

Regarding hardware-related fault injection such as bit flips, Kanawati et al. [24] proposed FERRARI, a software system that emulates hardware faults. Han et al. [20] designed DOCTOR, which focuses on injecting hardware errors and network errors. Wei et al. [50] quantitatively evaluated the accuracy of intermediate code level fault injection with respect to assembly level fault injection for hardware-related errors.

Regarding high-level software error injection such as operating system faults, Lee et al. [28] presented SFIDA, which is used to evaluate the resilience of distributed applications on the Linux platform. Kao et al. [25] invented “FINE”, a fault injection and monitoring tool to inject both hardware-induced software errors and software faults. Kooiwe and Tanenbaum [48] presented HSFI, which takes execution context information into consideration for efficient fault injection decisions. Cotroneo et al. [14] proposed ProFiPy, a tool that is programmable to specify different fault models using a domain-specific language for fault injection in Python.

More related to our work, some fault injection approaches are related to system call invocation errors. Koopman and De-Vale [27] proposed Ballista, a testing system that generates invalid inputs for system call invocations in order to evaluate the exception handling effectiveness of POSIX operating systems. Vyukov [49] designed syzkaller, a tool that fuzzes system call invocation inputs in order to detect kernel bugs. Amarnath et al. [5] designed a QEMU-based fault injection framework to evaluate the dependability of system calls with respect to bit flips errors. Simonsson et al. [43] presented ChaosOrca, a chaos engineering system for dockerized applications.

Regarding the error models used by the related work above, they are either randomly generated or predefined by developers. PHOEBE exclusively focuses on injecting system call invocation errors, and its key originality is to design realistic error models from errors that naturally happen.

B. Chaos Engineering

Chaos engineering can be defined as doing high-level fault injection on the production system directly [9]. Netflix’s ChaosMonkey [12] randomly shuts down servers in production in order to verify the whole system’s reliability against a server crash. Then this methodology has been extended with other kinds of errors such as the OS level and the network errors [22], [35]. There is also application-level chaos engineering research: Sheridan et al. [40] presented a fault injection tool for cloud applications, where faults are resource stress or service outage; Zhang et al. [51] devised ChaosMachine, a chaos engineering system that analyzes a Java application’s exception-handling capabilities in production.

To the best of our knowledge, none of the existing chaos engineering approaches synthesize realistic error models based on naturally happening errors like PHOEBE.

C. Observability

Monitoring techniques are most widely researched in the area of observability. Grobmann and Klug [19] proposed “PyMon”, a framework that monitors different computing architectures with a small footprint. Povedano-Molina et al. [37] designed DARGOS, a distributed architecture for resource management and monitoring in cloud computing. Arora et al. [7] presented a system called Parikshan that duplicates traffic into a copy of the production container, enabling the use of heavier monitoring tools without impacting the performance in production. Chang et al. [11] developed a Kubernetes-based monitoring platform for dynamic cloud resource provisioning. Enes et al. [15] proposed BDWatchdog, a solution for real-time analysis of big data frameworks and workloads that combines per-process resource monitoring and low-level profiling.

Another popular research direction in observability is tracing. Sigelman et al. [41] presented Google’s Dapper, a tracing infrastructure with low overhead and application-level transparency. Kaldor et al. [23] presented Canopy, Facebook’s end-to-end performance tracing infrastructure that enables developers to analyze performance data in real-time. Mace et al. [31] presented Pivot Tracing, which implements a happened-before join operator to enhance dynamic instrumentation and causal tracing. Instead of analyzing network requests in a distributed system, Coppik et al. [13] proposed TrEker, an approach that combines static and dynamic analyses to trace error propagation in OS kernels. Ren et al. [39] invented RepTrace, a framework that traces system calls in order to analyze the root causes of unreproducible builds. The traces of system call invocations also helps anomaly detection. Liu et al. [30] proposed a feature extraction method named STP that transforms the system call sequences into frequency sequences of n-grams in a trace to detect abnormal behavior.

Differently, PHOEBE focuses on the observability of system call invocation errors, which is not in the scope of this related work. Furthermore, PHOEBE synthesizes error injection models based on the monitoring observation. The combination of monitoring in production and fault injection is original.

VIII. Conclusion

In this paper, we have presented PHOEBE, a novel fault injection framework for reliability evaluation against system call invocation errors. The key novelty of PHOEBE is that it synthesizes and injects realistic system call errors, meaning that the injected errors are based on focusing on errors that naturally happen. By evaluating PHOEBE’s functionality and performance on two medium-sized real-world applications (email server, file transfer), we have shown that it is able 1) to detect reliability weaknesses 2) with low overhead. In the future, we will study the relationship between low-level system call invocation errors and high-level Java exceptions. This would developers to identify concrete locations in the application source code to fix the reliability weaknesses detected by PHOEBE.
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