Compositional Fuzzing
Aided by Targeted Symbolic Execution

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Abstract
Guided fuzzing has, in recent years, been able to uncover many new vulnerabilities in real-world software due to its fast input mutation strategies guided by path-coverage. However, most fuzzers are unable to achieve high coverage in deeper parts of programs. Moreover, fuzzers heavily rely on the diversity of the seed inputs, often manually provided, to be able to produce meaningful results.

In this paper, we present Wildfire, a novel open-source compositional fuzzing framework. Wildfire finds vulnerabilities by fuzzing isolated functions in a C-program and, then, using targeted symbolic execution it determines the feasibility of exploitation for these vulnerabilities. Based on our evaluation of 23 open-source programs (nearly 1 million LOC), we show that Wildfire, as a result of the increased coverage, finds more true-positives than baseline symbolic execution and fuzzing tools, as well as state-of-the-art coverage-guided tools, in only 10% of the analysis time taken by them. Additionally, Wildfire finds many other potential vulnerabilities whose feasibility can be determined compositionally to confirm if they are false-positives. Wildfire could also reproduce all of the known vulnerabilities and found several previously-unknown vulnerabilities in three open-source libraries.

Keywords: Vulnerability analysis, Source-code coverage, Fuzzing, Symbolic execution, Compositional analysis

1. Introduction
Fuzzing and symbolic execution are the two most popular techniques for automatically generating test-cases and finding vulnerabilities that have had a significant impact in the form of data and economic loss [50]. Fuzzing, in particular, has recently been very successful [30, 42, 4] in revealing exploitable vulnerabilities in open-source and widely used software, that exposed them to severe security-related implications, such as buffer-overflows. Fuzzing tools, such...
as AFL [54] and Peach [5], employ mutation strategies that rapidly change the user-supplied seed-inputs based on some heuristics. With appropriate instrumentation and fast mutation of inputs, the fuzzer may trigger interesting parts in the code where improper input handling may lead to a program crash, hang, or other undesirable behaviours. Most of the vulnerabilities found by fuzzers, however, are located in parts of the code that is relatively easy to reach [22, 34] for randomly mutated input data. The more complex parts of the program, which are guarded by branching conditions that cannot be satisfied by most random mutations are not reached, and hence not sufficiently explored, by the state-of-the-art fuzzers.

On the whitebox analysis side, symbolic execution [24], and their practical approaches such as concolic execution [40, 11] and whitebox fuzzing [23], suffer from the well-known path-explosion problem [10] due to which execution gets stuck in the shallow branches. Compositional analysis has been proposed in the past [37, 6] as a technique to alleviate the path-explosion problem in symbolic execution. It analyzes individual components that make up a larger system and, then, prunes away those paths in the program that do not lead to interesting executions of those components, such as vulnerability triggers. Results show [15, 32] that compositional analysis is trivially able to cover more parts of the program than plain symbolic execution and also, indeed, discovers more vulnerabilities in programs.

Fuzzing has not been, to the best of our knowledge, considered as a viable option for compositional analysis yet. We aim to bridge this research gap in this paper. The goal of our work is to improve vulnerability detection capability of fuzzers through increasing coverage in isolated functions. We define isolated functions as those functions that are parameterized, i.e. \( g(\text{int } a) \) can be isolated but not \( g(\text{void}) \). Our central premise is that, as shown by previous works [32, 22], higher coverage in isolated functions leads to an increase in discovered vulnerabilities as well. Then, our methodology employs targeted symbolic execution to perform a reachability analysis for the vulnerabilities discovered by fuzzing, so that we may confirm which vulnerabilities can also be exploited from higher level calling contexts.

**Problem.** Even though state-of-the-art fuzzers are capable of effectively finding vulnerabilities in programs that accept input from files or standard input, the line coverage achieved by these fuzzers is insufficient. In particular, as shown by previous studies [34], the coverage of functions lying deeper in the call-graph of the program is very low for fuzzers. As a result, these fuzzers miss many vulnerabilities in deep-lying parts of programs.

**Solution.** Drawing inspiration from past works in the improvement of plain symbolic execution [15, 20], we present a compositional analysis approach for fuzzing large real-world programs. We, first of all, fuzz isolated functions using automatically generated seed-inputs. In this step, functions at all depths of the program’s call-graph can be covered. Next, the framework summarises the vulnerabilities found by the fuzzer in isolated functions and replaces the
respective functions by their summaries. Finally, we use targeted symbolic execution to determine whether the vulnerabilities in isolated functions can be triggered by their parent (calling) functions, with the process repeated till a top-level function, such as `main`, is reached. This way, we can determine to a high degree of confidence whether a vulnerability in an isolated function may be a false-positive because the calling arguments are sanitised in the parent functions.

**Contribution.** In this paper, we have made the following main contributions

1. We describe a novel *compositional fuzzing* technique for finding vulnerabilities in programs using a combination of fuzzing and targeted symbolic execution.

2. The design of fuzzing drivers, described in section 5, can automatically generate seed inputs for any previously-unknown program, even if the goal may be to apply a fuzzer without compositional analysis.

3. The design and implementation of the framework can effectively make use of parallel cores, making it more scalable and efficient to find vulnerabilities in large-scale programs, than state-of-the-art fuzzers and symbolic execution engines.

4. Our evaluation of various open-source programs demonstrates that Wildfire can find more vulnerabilities than symbolic execution and fuzzing, through higher coverage in less time. Secondly, using three case studies, we show that compositional fuzzing can reproduce almost all exploitable vulnerabilities in open-source libraries and find new ones.

5. The accompanying tool, *Wildfire*[^1] implements the techniques described in this paper for C-programs, and is the first of its kind in hybrid (involving fuzzing and symbolic execution) compositional analysis tools. We have released Wildfire as an open-source tool.

We start this paper by briefly introducing the background to our methodology in section 2. Then, using a real-world example of a program, we motivate the problem-statement in section 3. In section 4, we list some related work to our research of symbolic execution, fuzzing and compositional analysis. Our methodology is, then, described in section 5 followed by some implementation details in section 6. In section 7 we evaluate Wildfire based on three research questions and list some limitations in section 8. In section 9 we conclude the paper.

[^1]: Wildfire or, more precisely, Macke-with-Wildfire-mode can be downloaded for free at [https://github.com/tum-i22/macke](https://github.com/tum-i22/macke)
2. Background

Before describing our compositional analysis approach we, first, describe the essential background of the underlying techniques of our methodology – fuzzing and targeted symbolic execution.

2.1. Fuzzing

Fuzzing is an automated testing technique \cite{46, 49} that makes use of mutations of seed inputs to execute the program under test and observe the return values and the external state of the system. It is known as a blackbox technique because it does not rely on information about the internal constraint-systems of the program but employs mutation strategies that change individual or groups of bits in the seed inputs to discover new paths in the program. The advantage fuzzing has over whitebox analysis techniques is that, due to the fast mutation strategies that do not depend on solving path-constraints, fuzzing can generate quickly invalid data to trigger vulnerabilities in programs, thereby causing unwanted behaviour, such as program crash. As a result, fuzzers can find many real vulnerabilities \cite{30, 47, 7} in programs that may be missed by other means of analysis.

2.2. Targeted Symbolic Execution

Symbolic execution \cite{24} is a whitebox automated testing technique that collects path-constraints along a program path from an entry point (e.g. main function) to an exit point (e.g. return statement) and solves these constraints using a constraint solver (e.g. SMT solver) to generate concrete test-cases that execute the respective path. Most symbolic execution engines, such as KLEE \cite{11} and Mayhem \cite{12}, employ a path-exploration strategy that prioritises unseen paths in the program. However, in many cases, inputs need to be generated that will trigger specific functionality or known areas of interest in a program, such as payload processing \cite{22} or patches \cite{29} that may potentially break existing functionality. In these cases, the symbolic execution engine needs to prioritise those paths that lead to the target of interest instead of new paths only. Various techniques \cite{27, 32, 51} have been suggested in the past for effectively focussing symbolic execution towards interesting areas of code. In addition to finding inputs for reaching targets of interest, targeted symbolic execution also helps in reducing the path-explosion problem, that is one of the main bottlenecks for classical symbolic execution techniques.

3. Motivation

Having described the background of fuzzing and symbolic execution we will now motivate our problem statement by referring to a vulnerability in a commonly used UNIX tool, Bzip2\footnote{www.bzip2.org}. Bzip2 is a UNIX tool for compressing and
decompressing files using a block-sorting compression algorithm, accompanied by an API (Libbzip2) that developers may use in their programs. The existence of such an API indicates a need for extensive testing of the library, because there may be many potential entry points to the library, not only the main function, resulting in a large attack surface.

Listing 1: Code of the function BZ2_hbCreateDecodeTables

```c
void BZ2_hbCreateDecodeTables ( Int32 *limit,
                                   Int32 *base, Int32 *perm, UChar *length,
                                   Int32 minLen, Int32 maxLen, Int32 alphaSize)
{
    Int32 pp, i, j, vec;
    pp = 0;
    for ( i = minLen; i <= maxLen; i++)
        for ( j = 0; j < alphaSize; j++)
            if (length[j] == i) { perm[pp] = j; pp++; }
    /* some more processing omitted here */
}
```

Listing 1 shows a condensed version of the code of Bz2_hbCreateDecodeTables function of Bzip2, that has a potential vulnerability in line 11. Basically, if the value of parameter, alphaSize, is bigger than the size of the buffer, length, an attacker can cause a buffer-overflow on line 11 (j >= sizeof(length)) resulting in a program crash, i.e. denial-of-service. One possible sequence of function calls that can lead to BZ2_hbCreateDecodeTables is shown in figure 1. One would expect there to be a check on the alphaSize variable (whether it is less than the size of length) in at least one of the functions between main and BZ2_hbCreateDecodeTables. However, upon inspecting the code of all these functions, we discovered that such a check simply does not exist, i.e. the vulnerability in line 11 can be exploited from main.

We ran KLEE [11] (with default path-search strategy) and AFL [54] (with

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3This vulnerability has already been reported to, and acknowledged by, secteam at FreeBSD project and the author of Bzip2. We are currently awaiting analysis for a CVE.
5 unique compressed files, as seed input) on Bzip2 for 2 hours\(^4\) and 10 hours, respectively. To make the path exploration more focused for discovering our target function of \texttt{BZ2.hbCreateDecodeTables}, we supplied the “-d” flag, which forces decompression (calling the \texttt{uncompress} function) without necessarily performing expensive initialization.

We found that neither KLEE nor AFL was able to spot the vulnerability in \texttt{BZ2.hbCreateDecodeTables} function. Only two functions between \texttt{main} and \texttt{BZ2.hbCreateDecodeTables} (marked in grey in figure 1) were covered by, both, KLEE and AFL and due to this, the vulnerable instruction was never executed and the vulnerability not found.

The above demonstrates the limitation of fuzzing and symbolic execution tools in achieving reasonable path coverage in programs that take as input files or data-structures encoded in a particular format, such as block-sorted files. Because of potentially complex branching-conditions in the \texttt{uncompress} function, AFL cannot mutate our seed inputs to pass them and reach the \texttt{uncompressStream} function. Symbolic execution, on the other hand, also had to deal with path-explosion in the \texttt{main} and \texttt{uncompressStream} functions, and could never cross them to reach \texttt{uncompressStream}. In this paper, we describe a method to force coverage of almost all functions in programs like Bzip2, while also being able to determine whether potential vulnerabilities, such as the one in \texttt{BZ2.hbCreateDecodeTables}, can be exploited.

4. Related Work

4.1. Fuzzing tools and advancements

Fuzzing \cite{46} is a greybox strategy, often guided by lightweight instrumentation \cite{54}, to generate test-cases for a program. Libfuzzer \cite{44} is a fuzzing tool for libraries and arbitrary functions using an \textit{in-process} and coverage-guided fuzzing algorithm based on AFL \cite{54}. However, due to the in-process nature of Libfuzzer where the fuzzing logic is executed for each iteration in the same process as the target application, Libfuzzer cannot recover automatically after finding a crashing input. Due to the above, Libfuzzer was not a suitable choice of fuzzing tool in Wildfire, because it would be too expensive to restart the fuzzer process for every crashing execution in isolated functions. Several state-of-the-art fuzzers such as AFLFast \cite{7}, Honggfuzz \cite{48}, Peach \cite{3}, and Vuzzer \cite{38} have been developed in the past decade alone that have specialized optimizations in terms of directed path search \cite{8}, guided seed selection \cite{39} and controlled frequency of path selection \cite{13, 53}. Many of these advanced fuzzers have also found several previously unknown vulnerabilities \cite{7}.

4.2. Compositional Analysis

To handle the issues of path-explosion and constraint-solving in symbolic execution \cite{10}, several approaches have been proposed of which compositional
analysis \cite{32,15,41,21,36} is one. Breaking down a larger program into smaller modules has shown to improve \cite{20,41,28,51} the structural coverage of symbolic execution engines, as expected. With the compositional analysis of discovered vulnerabilities (using targeted symbolic execution \cite{27}), some techniques \cite{16,15,32} can also report the extent to which the calling functions are affected. The only open-source compositional analysis tool we could obtain for comparison was Macke \cite{32}. To the best of our knowledge, there has been no past work to explore fuzzing, instead of symbolic execution or static analysis \cite{19}, as a possible strategy for finding vulnerabilities in isolated functions. In addition to extensive evaluation of compositional analysis, such a fuzzing-based compositional analysis technique is our main contribution.

4.3. Hybrid Fuzzing and Symbolic Execution

Driller \cite{45} is a hybrid tool that employs selective symbolic execution to help the fuzzer overcome saturation w.r.t. new paths discovered. It was able to discover many previously unknown vulnerabilities and performed especially well on the Darpa Cyber Grand Challenge dataset. Taintscope \cite{52} and BuzzFuzz \cite{18} employed dynamic taint tracking, to focus fuzzing on interesting byte-regions of input that may affect suspicious regions of the code. Böttiger and Eckert \cite{9} presented DeepFuzz, a tool that finds vulnerabilities in binaries by using symbolic execution to estimate the probability of exploring new paths with a seed mutation during fuzzing. Munch \cite{34} is a hybrid tool introduced to increase function coverage by employing two combinations of symbolic execution and fuzzing – fuzzing with seed-inputs generated by symbolic execution, and targeted symbolic execution when fuzzing saturates. Finally, Pak \cite{35} presented a hybrid method to feed the fuzzers with inputs generated by symbolic execution by solving the path-constraints after a new branch has been visited. As mentioned before, none of these hybrid works analyzes isolated components, but only applied at the single entry-point of programs. An alternative to our hybrid and compositional approach would have been to use state-of-the-art methods such as symbolic execution to find vulnerabilities in isolated components, just like Macke \cite{32}, and confirm the feasibility of vulnerabilities by biasing a mutation-based fuzzer, as done in AFLGo \cite{8}, towards generating inputs to execute the target vulnerabilities. This is an orthogonal approach to our technique and, therefore, will not be discussed in this paper.

There are, to the best of our knowledge, no previous solutions based on compositional analysis to overcome the known difficulties of fuzzing (insufficient path-coverage) and symbolic execution (path-explosion and constraint solving). Wildfire plugs this gap in hybrid research.

5. Compositional Fuzzing – Methodology

We will now describe the design of our compositional fuzzing framework, Wildfire, and its components.
Figure 2: Technical design of Wildfire

5.1. Overview

The technical design of our framework, Wildfire, is shown in figure 2. In this figure, the steps of our framework and their inputs and outputs are shown in white boxes, which we will discuss first. The specific tools and implementation details to assist in various tasks are shown in grey/black boxes and boxed-arrows that we will discuss in section 6.

The workflow of Wildfire consists of the following, in order:

1. **Instrumentation and compilation** of the source-code to LLVM intermediate representation.

2. **Generating fuzzing drivers** to populate seed-inputs for isolated functions and to extract function arguments from the inputs generated by the fuzzer.

3. **Generating test-cases with fuzzing** of the drivers generated in the previous step, for isolated functions.

4. **Generating crash reports** by replaying the test-cases generated by a fuzzer on an address-sanitised version of the program and reporting vulnerabilities.

5. **Summarizing functions** and replacing the isolated functions with their respective summaries, thereby condensing functions to only the paths leading to potential vulnerabilities.

6. **Determining feasibility analysis of discovered vulnerabilities** using stack-trace matching and targeted symbolic execution to generate recursively, until the main function or an API is reached, concrete arguments to trigger the vulnerabilities.

We now describe all but the first steps in more detail below. The first step is a trivial compilation procedure for LLVM. However, the description of compiled objects, as shown in figure 2, will be presented in section 6.
5.2. Generating Fuzzing Drivers

To fuzz isolated functions in a program, Wildfire needs to generate fuzzing drivers that act as wrappers around these functions, to 1. given the parameter list, generate seed-inputs (known, from now on, as seed-arguments) for the function, and 2. correctly assign the inputs generated by the fuzzer to the function arguments. We will now describe the design of driver generation w.r.t. both requirements listed above.

5.2.1. Seed-argument Generation

Various possibilities, such as thresholded symbolic execution \[35, 34\] and taint analysis \[18, 52\] have been proposed to generate seed-inputs for fuzzing. However, while they may be useful for programs containing many parsing functions, the overhead of symbolic execution is too high for our approach where we directly fuzz isolated functions. We prefer to generate seed-arguments statically, i.e. without executing the function first. We propose two methods to generate seed-arguments for isolated functions. In the first method, Wildfire generates two byte-streams – an empty stream and a stream consisting of random characters from the English alphabet, \([a–z]\). Providing a random character is important because we cannot fuzz a target if all the seed-inputs lead to a program crash or hang (due to the limitation imposed by our fuzzer, as discussed in section \(6\)). For a parameter of pointer type, a function is more likely to crash due to buffer-overflow with an empty byte-stream than with a non-empty one. In the second method for generating seed-arguments, Wildfire generates a byte-stream with as many delimiter characters in the seed-argument byte-stream as there are parameters for the function. As we will see in section \(5.2.2\) the delimiter character determines the start and end within a byte-stream between which an argument must be extracted.

5.2.2. Argument Extraction

![Diagram of function argument extraction from a byte-stream.]

The input provided by the fuzzer, including seed-arguments, is a byte-stream. We need to extract bytes from this byte-stream (and cast, if necessary) and assign to function arguments. Two example scenarios for argument extraction from a byte-stream are shown in figure \(3\). Our method, first and foremost, distinguishes function parameters as one of two types - non-pointer and pointer data-type. We will ignore any functions with parameters with double- or more
pointers. This is a limitation in our framework, and we will discuss this further in section 8.

The first scenario depicted in figure 3 is that of a function foo that accepts two non-pointer type (integer) arguments. In algorithm 1, we show the algorithm for extracting non-pointer type arguments, such as int or char. The ExtractFixedSizedArgument function simply copies typeSize number of bytes (line 4 in algorithm 1) from the byte-stream to the argument and casts it to the required type. If there are not at-least typeSize number of bytes left in the stream to consume, the stream is padded with null character bytes, as shown in lines 8 and 9. The next scenario depicted in figure 3 is that of a function.

Algorithm 1 Algorithm for extracting non-pointer arguments

```
procedure ExtractFixedSizedArgument(int typeSize, char[] remData, int remSize)
    type [] t
    if typeSize ≤ remSize then
        t ← type(remData[:typeSize])
        remData ← remData[typeSize :]
        remSize ← remSize − typeSize
    else
        memset(t, '\0', typeSize)
        t[0 : remSize] ← remData
        remData ← []
        remSize ← 0
    end if
    return type(t)
end procedure
```

Algorithm 2 Algorithm for extracting pointer arguments

```
procedure ExtractDynamicSizedArgument(int typeSize, char[] remData, int remSize)
    type [] t, int bufSize, int givenSize
    givenSize ← LookForDelimiter(remData, remSize)
    bufSize ← RoundDown(givenSize, typeSize)
    t ← remData[:bufSize]
    if (bufSize ≤ remSize) then
        remSize ← remSize − givenSize
        remData ← remData[givenSize :]
    else
        remData ← []
        remSize ← 0
    end if
    return t
end procedure
```

function bar that accepts one pointer type (integer pointer) and one non-pointer type argument. For parameters of pointer type, our approach is based on a special delimiter character (assumed to be “//” in figure 3) in the byte-stream that splits it for assigning to dynamically-sized parameter types. As shown in algorithm 2 for each pointer type argument, ExtractDynamicSizedArgument copies the input byte-stream to t (line 5) till the first delimiter character is encountered, or the end of byte-stream has been reached. The helper function, LookForDelimiter (line 3) returns the location of the first delimiter character in the leftover byte-stream, or the end of the stream, whichever comes first. RoundDown rounds givenSize down to a multiple of typeSize.
5.3. Generating Test-cases using Parallel Fuzzing

After generating fuzzing drivers, the next step in our framework is to apply the fuzzer to the isolated functions with the generated seed-arguments. The inputs to fuzzing are the generated drivers (implying, directly, the function) which, as described in section 5.2, can be directly executed by the fuzzer. This step can be run in parallel for all isolated functions because the calling contexts of the isolated functions are ignored for now.

For all isolated functions, the output of this step is a list, $T_f$, of all test-cases generated by the fuzzer for function, $f$.

$$T_f = \{t_1, t_2, \ldots, t_n\}, \quad (1)$$

where $n$ is the number of unique test-cases generated by the fuzzer. If the function $f$ accepts $m$ arguments, then,

$$t_i = \langle I_{i_1}, I_{i_2}, \ldots, I_{i_m} \rangle, \quad (2)$$

where $I_{i_k}$ is the $k^{th}$ argument.

5.4. Generating Crash Reports using Test-cases Replay

Fuzzing of isolated functions is carried out on a lightweight compiled object, without heavy instrumentation. Therefore, to obtain crash-reports that include the function’s arguments and the stack-trace of crashing executions, we must obtain details of all crashing (due to discovered vulnerabilities) executions to be passed to the next steps. To do this, the first step is to minimize the set of all generated test-cases, using `afl-cmin` [1] and `afl-tmin` [3]. These two programs reduce the size of an input corpus by 1. removing inputs that execute redundant paths in the program, and 2. removing starting and trailing null bytes from an input byte-stream while keeping the executed path unchanged.

Then, we pass the minimised set of test-cases to an instrumented version of the compiled object that gracefully handles crashing executions due to buffer-overflows, illegal pointer operations or null-pointer dereferencing. The input to this step, as shown in figure 2, are the test-cases generated by the fuzzer in section 5.3. The first output of this step is the list, $T'_f$, of all test-cases (arguments) that result in a program crash. The second output of this step is a set of stack-traces for crashes reported in the isolated functions. A stack-trace, $S_{f_0}$, of a crashing execution of the function, $f_0$, with arguments, $t_i$ (equation (1)), is an ordered set

$$S_{f_0}(t_i) = \langle L(f_0), L(f_1), L(f_2), \ldots L(f_n) \rangle, \quad (3)$$

where $f_i$ calls $f_{i+1}$. Here, $L$ returns the vulnerable instruction (line number) and name of the function.

We call all buffer-overflows, null-pointer dereferences and other index-out-of-bounds memory operations reported in the crashing function as vulnerabilities and an isolated function that contains at least one vulnerability as a vulnerable function.
5.5. Summarizing Vulnerable Functions

After generating crash reports for vulnerable functions, Wildfire replaces the isolated functions with a summary of the crash reports, to allow targeted symbolic execution for some of them. The rationale behind this step is to tackle the path-explosion problem in symbolic execution. To assist the symbolic execution engine in not getting stuck due to path-explosion, we replace the set of paths in a vulnerable function by just the set of value-assignments for its arguments that will trigger the vulnerabilities.

Let, for a vulnerable function $f_0$, the parameter list be $P$.

$$P = (p_1, p_2, \ldots, p_m), \quad (4)$$

where $p_i$ is the $i^{th}$ formal parameter for $f_0$. Then, the summary, $f_{\text{summary}}$, generated for the $f_0$ is as shown in algorithm 3.

**Algorithm 3** Summary of a vulnerable function, $f$

1: function $f_{\text{summary}}(P)$
2: assert $(P \neq t_1)$
3: assert $(P \neq t_2)$
4: \vdots
5: assert $(P \neq t_n)$
6: return $f(P)$
7: end function

In algorithm 3, $t_i$ is as described by equation (2). The equality $P == t_i$ is defined as follows

$$P == t_i \iff (p_1 == I_{i_1} \land p_2 == I_{i_2} \land \ldots p_m == I_{i_m}), \quad (5)$$

where the term $I_{i_k}$ is also defined in equation (2). The inequality $P \neq t_i$, then, is the negation of the equality above.

Intuitively, the function summaries simply compare the formal parameters with concrete argument values that were found to trigger a vulnerability. For pointer data-types, this entails comparing the exact content of the allocated memory using `memcmp`. We assert a *negation* of equality because, then, Wildfire would report an assertion error (and stops further processing) when there is a match found for $P$ that is equal to $t_i$. Such an assertion error implies that the vulnerability in $f$ can, indeed, be triggered from a calling function of $f$. If there is no assertion-error (calling function cannot generate crashing inputs), we proceed with the processing by calling the original function $f$, as intended, to ensure that we include its side effects on the function and its variables. Please note that, unlike previous work, such as [37, 28], where formal parameters are compared to the input pre-conditions (in the form of constraint systems), our technique would only match the concrete values of the arguments, because we are limited by the fuzzer, which only generates concrete inputs and not general path-constraints.
5.6. Determining Feasibility of Reported Vulnerabilities

After finding and reporting potential vulnerabilities in isolated functions, any compositional analysis framework needs to determine whether these vulnerabilities can be exploited in a real usage of the program, e.g. through a program’s API. This determination of exploitation can be done pairwise for functions, i.e. can a vulnerability in function $f$ be exploited from functions that call $f$ and, if yes, can it exploited from the functions that call the functions that call $f$, and so on till an interface function is reached. Wildfire performs the above determination in two phases, which we will now describe.

5.6.1. Phase 1: Stack-trace Matching

As explained in section 5.4, the crash reports generated by the address-sanitized version of the program contain stack-traces of crashing executions of isolated functions. Our framework, in this phase, determines that a vulnerability in $f_a$ can be exploited by $f_b$ if there were at least two matching stack-traces, $S_{f_a}$ and $S_{f_b}$. We call two stack-traces, $S_{f_a}$ and $S_{f_b}$, matching \([32]\) if $S_{f_a} \subseteq_O S_{f_b}$. Here $\subseteq_O$ denotes an ordered subset, meaning that the elements in the smaller set occur in the same sequence as in the larger set. Intuitively, this phase of feasibility determination checks if a crashing execution of a function, $f_b$, is due to the same vulnerable instruction as another crashing execution of function $f_a$ that will, potentially, be called by $f_b$.

5.6.2. Phase 2: Targeted Symbolic Execution

A pair of matching stack-traces, $S_{f_a}$ and $S_{f_b}$, in phase 1 implies that fuzzing was able to cover the path in $f_b$ that leads to the vulnerable function, $f_a$, with arguments triggering the vulnerability. However, if no such matching stack-trace can be found for $S_{f_a}$, it might be because the fuzzer was not able to generate any test-cases to trigger the said path, and not merely because such a path does not exist. In phase 2, Wildfire tries to exploit the vulnerable functions from calling functions using symbolic execution to target only those vulnerable functions for which no matching stack-traces were found in phase 1.

Phase 2 of feasibility determination takes as input the function summaries, $f_{summary}$, generated in section 5.5. After replacing the function bodies with their summaries, we use targeted symbolic execution from parent functions to find paths leading to a vulnerable function. Consider again a vulnerable function $f_a$, for which phase 1 did not find any matching stack-trace. In phase 2, all functions, $f_b$, that potentially call $f_a$ are symbolically executed by our framework where the target is set as $f_{summary}$, which is the summarized version of $f_a$. When a targeted search strategy is applied, all those branches are ignored (based on distance in the control-flow graph) that do not potentially lead to the target. In contrast to the explore-new-paths-first \([11]\) strategy, which is commonly the default in symbolic execution engines, a targeted symbolic execution is less likely to get stuck due to path-explosion because it eliminates uninteresting paths as soon as it can determine that they would never lead to the target. Additionally, the function summary $f_{summary}$ also has fewer paths
to explore than the original function, $f_a$. In this phase, therefore, we increase our chances of determining if a vulnerability found in $f_a$ can also be exploited from functions, $f_b$, that potentially call $f_a$.

Wildfire applies both, phase 1 and phase 2, recursively until the main function or a library’s API functions are reached. The output of this stage is a list of vulnerability reports, each containing the vulnerable instruction, function and the chain of functions through which it is feasible to exploit it.

6. Implementation

**Different LLVM Versions.** It was necessary for our framework to compile the program-under-test to two target objects, LLVM 3.4 and 6.0 [25] bitcodes. This was because the choice of our fuzzing and symbolic execution tools could only accept LLVM 6.0 and LLVM 3.4 bitcodes, respectively. Moreover, to insert dynamic instrumentation, we could only use intermediate LLVM representations and not binaries.

**AFL for Fuzzing.** For fuzzing isolated functions, we use AFL [54], which is a state-of-the-art fuzzing tool for binaries and LLVM. We make use of the deferred instrumentation mode in AFL [2] that lets us dynamically dictate to the fuzzer that the driver selection (which functions to fuzz), should be skipped and only the original function body must be fuzzed.

**ASAN for Generating Crash Reports.** Using Opt, we insert ASAN [43] instrumentation into LLVM 6.0 bitcode. The test-cases generated by AFL are sent as inputs to this ASAN instrumented version of the program to obtain crash reports caused by illegal memory-related operations, such as buffer-overflow or use-after-free, as described in section 5.4.

**KLEE22 for Symbolic Execution.** Our choice of symbolic execution tool for determining the feasibility of vulnerabilities is KLEE22 [32]. KLEE22 is a custom fork of KLEE [11], which implements targeted-search based on arbitrary function-calls in a program.

7. Evaluation

We will now describe the experiments, metrics, results and, finally, a synthesis of our observations.

7.1. Comparison Baseline

We start the description of our experiments by listing the tools that we will compare with Wildfire. There exist many competing frameworks and tools, such as Driller [45], AFLGo [8], FairFuzz [26] and Angora [14], that have proposed many improvements over state-of-the-art mutation-based fuzzing. However, we picked our baseline tools mainly based on whether a tool 1. was available as an open-source tool, 2. had reasonably complex user-guide or documentation,
and could be used “out-of-the-box” for our analysed programs, and 3. promised a higher coverage or higher rate of vulnerability-discovery for general-purpose UNIX-based programs, compared to other techniques.

With the above inclusion criteria in sight, we concretely divide the state-of-the-art, and comparative, tools in the following three categories.

1. **Basic tools:** The first set of tools that we will compare with are basic symbolic execution and fuzzing tools. For symbolic execution, we will pick *KLEE* \[11\] and for fuzzing, we will pick *AFL* \[54\]. Both of these tools are considered state-of-the-art in the fundamental techniques used in this paper.

2. **Coverage-guided tools:** Next, we include more sophisticated tools involving symbolic execution and fuzzing, that improve upon these fundamental techniques by actively monitoring structural coverage of the program-under-test. We will pick *AFLFast* \[7\] and *Munch* \[34\] in this category. More details on these tools can be found in section 4.

3. **Compositional tool:** Finally, we include *Macke* \[32\], which is the only other compositional analysis tool, to the best of our knowledge, which is open-source and available out-of-the-box for C-language programs. We must mention here, for the sake of full disclosure, that Macke and Wildfire are based on the same underlying technologies, as described in section 4. But they differ, specifically, in how vulnerabilities are discovered in isolated components (section 5.3), arguments are extracted from byte-streams (section 5.2.2), test-cases are replayed (section 5.4) and functions are summarized in terms of discovered vulnerabilities (section 5.5).

### 7.2. Research Questions

To evaluate Wildfire, we will try to answer the following research questions

**RQ1** How does the in-depth coverage of analysed programs by Wildfire compare to those of the basic and coverage-guided tools?

**RQ2** Following from coverage, how does the vulnerability finding capability of Wildfire compare to those of the basic, compositional and coverage-guided tools?

**RQ3** Can Wildfire be used to effectively test libraries without manual intervention, such as writing drivers?

### 7.3. Experimental Setup

For answering the research questions, we selected 8 open-source C programs and 12 GNU Binutils, listed in table 1 for RQ1 and RQ2. In terms of LOC and functions, this set contains a wide range from basic utilities to much larger programs. For answering RQ3, we selected three case studies (table 1) of open-source libraries.
Table 1: Open-source programs analyzed

| Prog.# | Program     | LOC | Functions | Analysis time (minutes) |
|--------|-------------|-----|-----------|-------------------------|
| 1      | bc 1.06     | 3.5k| 129       | 22.5                    | 283.2       |
| 2      | bzip2 1.0.6 | 3.3k| 108       | 36.4                    | 383.3       |
| 3      | diff 3.4    | 7.8k| 391       | 103.0                   | 849.9       |
| 4      | flex 2.6.0  | 6.5k| 260       | 58.0                    | 716.6       |
| 5      | grep 2.25   | 8.0k| 461       | 130.5                   | 933.3       |
| 6      | less 481    | 7.9k| 459       | 66.7                    | 800.1       |
| 7      | lex r131    | 4.7k| 205       | 68.6                    | 999.9       |
| 8      | sed 4.2.2   | 3.2k| 213       | 57.9                    | 349.9       |

**Binutils 2.31.1**

| Prog.# | Program     | LOC | Functions | Analysis time (minutes) |
|--------|-------------|-----|-----------|-------------------------|
| 9      | addr2line   | 49.0k| 1485      | 607.0                   | 1440.2      |
| 10     | ar          | 50.2k| 1547      | 605.0                   | 1584.0      |
| 11     | as          | 65.8k| 2088      | 603.2                   | 1584.1      |
| 12     | cxxfilt     | 48.9k| 1484      | 274.3                   | 1584.0      |
| 13     | gprof       | 51.2k| 1540      | 404.4                   | 1439.9      |
| 14     | ld          | 64.3k| 1953      | 510.2                   | 1440.3      |
| 15     | nm          | 49.5k| 1509      | 383.4                   | 1440.3      |
| 16     | objcopy     | 56.2k| 1656      | 187.1                   | 1584.1      |
| 17     | objdump     | 64.5k| 1876      | 234.2                   | 1584.0      |
| 18     | ranlib      | 50.3k| 1547      | 394.0                   | 1440.3      |
| 19     | readelf     | 17.5k| 249       | 42.9                    | 514.8       |
| 20     | size        | 49.1k| 1491      | 380.5                   | 1439.9      |

**Libraries**

| Prog.# | Program     | LOC | Functions | Analysis time (minutes) |
|--------|-------------|-----|-----------|-------------------------|
| 21     | Libtiff 4.0.9 | 82.7k| 639       | 368.0                   | –           |
| 22     | Libpng      | 43.8k| 516       | 360.0                   | –           |
| 23     | Libcurl 7.59.0 | 209.2k| 692       | 680.0                   | –           |

We repeated all experiments five times[^1] on an Intel Xeon CPU E5-1650 v2 with 12 cores, 3.50GHz per core, 126 GB of RAM, and running 64-bit Ubuntu 16.04.4 LTS.

In each repetition, we allowed Wildfire to fuzz each isolated function for 60 seconds each (maximum) and we gave each run of targeted-search a total of 60 seconds to reach the vulnerable function and trigger the vulnerability. For comparison, we ran Macke [32] for the same amount of time as Wildfire. Generation of test-cases for functions could be carried out in parallel (section 5.3) for isolated functions in Wildfire and Macke, i.e. all 12 cores could be utilised at the same time. Therefore, for a fair comparison, we allowed the other baseline tools, KLEE [11], AFL [54], AFLFast [7] and Munch [34], to run for approximately 12 times the total time taken by Wildfire or 24 hours, whichever was smaller. Times taken in each repetition of every benchmarked program are listed in table 1.

[^1]: Due to reasonably limited resources and long experiment times ($\approx 13$ hours per repetition per benchmark, per tool) we could not perform more than 5 repetitions.
7.4. Coverage and Vulnerabilities

For evaluating coverage, we compare Wildfire to the basic and coverage-guided tools. For evaluating vulnerabilities, we compare Wildfire to basic, coverage-guided and compositional tools.

![Comparison of line coverage](image1.png)

**Figure 4: Comparison of line coverage**

![Comparison of function coverage](image2.png)

**Figure 5: Comparison of function coverage**

![Comparison of line coverage grouped by call-graph depth](image3.png)

**Figure 6: Comparison of line coverage grouped by call-graph depth**

Figure 4 shows the average (over 5 repetitions) line-coverage(%) achieved by Wildfire, KLEE, AFL, AFLFast and Munch in the given time-limits. Figure 5 shows the average (over 5 repetitions) function-coverage(%) achieved by
the same techniques. Figure 6 shows the average (over all functions and 5 repetitions) line-coverage at every depth of the call-graph of all programs, e.g. the lines of code in the `main` function are counted at \( x = 0 \) in figure 6 and so on. Please note that at every call-graph depth, we only averaged over those programs that contained at least one function at that depth.

Figures 4 to 6 show that the in-depth line coverage and function coverage for all programs is larger with Wildfire than plain symbolic execution and fuzzing, as implemented in KLEE and AFL, respectively, as well as advanced tools that improve upon these techniques based on coverage, viz. AFLFast and Munch. Wildfire even achieves higher coverage at \( depth = 0 \) due to the following reason — more lines in the `main` function are covered when targeted symbolic execution is used for determining feasibility of vulnerabilities, than when only fuzzing or symbolic execution is applied without a set target. The reason that function coverage was not 100\% for Wildfire was, as explained in section 5.2.2, that Wildfire does not fuzz functions that contain any parameter of double- or more pointer type. In this study, we take no measures to handle this case and, instead, rely on targeted symbolic execution in phase 2 (section 5.6) to generate test-cases for those functions that could not be fuzzed by AFL.

Table 2: Vulnerability-related metrics for Wildfire and the compositional tool

| Prog. | Vulnerabilities | \( |chain| > 1 \) | \( chain < P^2 \) |
|-------|-----------------|----------------|-----------------|
|       | Wildfire Macke  | Wildfire Macke | Wildfire Macke |
| bc    | 72   57         | 42   30         | 7   16          |
| bzip2 | 96   71         | 33   22         | 0   0           |
| diff  | 219  256        | 205  166        | 32  7           |
| flex  | 124  106        | 46   40         | 3   12          |
| grep  | 319  261        | 186  132        | 24  7           |
| less  | 167  166        | 151  124        | 15  14          |
| l4    | 102  92         | 119  100        | 43  3           |
| sed   | 124  93         | 109  86         | 37  8           |
| addr2line | 979  804 | 404  226 | 10  9 |
| ar    | 983  794        | 386  234        | 10  8           |
| as    | 1230 1051       | 586  355        | 24  10          |
| cxxfilt | 895  811 | 294  234 | 4   6 |
| gprof | 982  837        | 398  238        | 9   6           |
| ld    | 1218 1005       | 522  326        | 15  13          |
| nm    | 948  847        | 362  247        | 10  7           |
| objcopy | 862  0         | 221  0         | 0   0           |
| objdump | 1008  0   | 258  0         | 0   0           |
| ranlib | 944  850       | 360  242        | 9   7           |
| readelf | 159  106       | 62   50         | 11  0           |
| size  | 948  791        | 375  216        | 9   9           |
| strings | 1106  0      | 550  0         | 10  0           |
| strip | 872  0         | 221  0         | 0   0           |

An increased coverage can be easily explained because we directly fuzz isolated functions. Let us now see how it affects vulnerability discovery. Table 2 lists the results related to vulnerability discovery for Wildfire and the only other
compositional analysis tool in our study, Macke [32]. For these two tools, we have listed in this table the following three measures – The column “Vulnerabilities” lists the total number of vulnerabilities found by these tools, determined by a uniquely vulnerable instruction (equation (3)). To determine whether any calling function could exploit the vulnerabilities discovered by Wildfire or Macke, we list the “$|\text{chain}| > 1$” criteria, listed in the next column, that counts only those vulnerabilities that can be, according to feasibility analysis (section 5.6), exploited by at least one calling function. Some of these chains were reported by simple stack-trace matching, as described in phase 1 of feasibility determination (section 5.6), while others were reported from targeted symbolic execution towards summarised functions in phase 2. The number of such chains whose ends (highest-level vulnerable functions) were reported by phase 2, and not by simple stack-trace matching, are listed in the next column in table 2 as “$\text{chain} \prec P_2$”.

We can see from table 2 that Wildfire was almost always (except diff) able to find more vulnerabilities than Macke. Moreover, the number of chains discovered by Wildfire with $|\text{chain}| > 1$ was also more than with Macke. Lastly, for most programs, Wildfire discovered as many, or more, chains of vulnerabilities with $\text{chain} \prec P_2$. From table 2 we can see that Wildfire performs better than, or the same as, Macke on most metrics described for compositional analysis tools.

![Figure 7: Distribution of vulnerability-chains’ lengths across all programs.](image)

72% of the vulnerabilities that could be exploited from main() required targeted symbolic execution to be found.

The total distribution of the lengths of chains of functions where a unique vulnerable instruction may be exploited, as per Wildfire, is shown in figure 7a. This distribution shows that Wildfire can generate chains of various lengths and, in fact, finds that about half of all discovered vulnerabilities can be exploited by at least one other function. In some cases, chains of 6 or more functions in the call-graph are also found. For 72% of all chains ending at the main function, targeted symbolic execution was necessary to trigger the vulnerabilities. Additionally, while the average length of all chains reported by Wildfire is $\approx 1.6$ (figure 7a), it is $\approx 2.6$ (figure 7b) for chains where $\text{chain} \prec P_2$. The above demonstrates the usefulness of combining targeted symbolic execution with isolated functions’ fuzzing for discovering high-impact vulnerabilities.

However, some of the vulnerabilities discovered by Wildfire or Macke may

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6 “$\text{chain} \prec P_2$” should be read as “chains ending with a function found by phase-2 of feasibility analysis.”
never be exploited because their calling functions might sanitise the inputs before calling the vulnerable functions. Therefore, as a final comparison with state-of-the-art tools, we present in Table 3 the count of vulnerabilities that could be triggered from the main function of a program. Since this factor can be measured for any baseline tool of our study, we have included basic tools (KLEE and AFL), coverage-guided tools (AFLFast and Munch), and compositional tool (Macke) for comparison.

Table 3: Vulnerability-related metrics for all baseline tools

| Prog. | Wildfire | KLEE | AFL | AFLFast | Munch | Macke |
|-------|----------|------|-----|---------|-------|-------|
| bc    | 3        | 0    | 1   | 1       | 0     | 5     |
| bzip2 | 0        | 0    | 0   | 0       | 0     | 0     |
| diff  | 2        | 0    | 0   | 0       | 0     | 2     |
| flex  | 0        | 0    | 1   | 1       | 1     | 0     |
| grep  | 0        | 0    | 0   | 0       | 0     | 0     |
| less  | 1        | 1    | 0   | 0       | 0     | 1     |
| lex   | 1        | 1    | 0   | 0       | 1     | 2     |
| sed   | 1        | 0    | 0   | 0       | 0     | 1     |
| addr2line | 1 | 0 | 0 | 0 | 0 | 1 |
| ar    | 0        | 0    | 0   | 0       | 0     | 0     |
| as    | 7        | 0    | 0   | 0       | 0     | 6     |
| cxz   | 0        | 0    | 0   | 0       | 0     | 0     |
| gprof | 0        | 0    | 0   | 0       | 0     | 0     |
| ld    | 3        | 3    | 1   | 1       | 2     | 3     |
| nm    | 2        | 1    | 0   | 0       | 1     | 2     |
| objcopy | 0     | 0    | 0   | 0       | 0     | 0     |
| objdump| 0        | 0    | 0   | 0       | 0     | 0     |
| ranlib| 0        | 0    | 0   | 0       | 0     | 0     |
| readelf| 0       | 0    | 0   | 0       | 0     | 0     |
| size  | 1        | 0    | 0   | 0       | 0     | 1     |
| Total | 22       | 6    | 3   | 3       | 5     | 24    |

We can see from Table 3 that for all but one (Flex will be explained later) programs, the number of such vulnerabilities found by Wildfire was higher than or equal to other baseline tools, in almost 90% less time (considering parallelism). However, for bc and lz4, Macke outperformed Wildfire and found 2 and 1 more vulnerability from main function, respectively.

Please also note that all the numbers in Table 2 and Table 3 are the common results from the five repetitions of Wildfire, KLEE, AFL, AFLFast, Munch and Macke, i.e. we only list those vulnerabilities and chains that were reported by all five runs of the respective method.

The Flex exception. We saw in Table 3 that AFL, AFLFast and Munch discovered more main vulnerabilities in Flex than Wildfire. In the code of Flex, the majority of the functionality is contained within a function that lie close to the main function, viz. flex_main function. Due to this fact, Wildfire should have given more time to this large function than other smaller functions, because the baseline tools get much more overall time to analyze this single function close to the entry point than Wildfire. We leave time-scaling based on the size of isolated-functions as future work.

Thus, we have shown, using 20 benchmarks, that a compositional fuzzing approach makes it more likely to discover vulnerabilities in a considerably shorter
time than basic and coverage-guided tools, by deliberately executing functions in isolation, and performing a bottom-up feasibility analysis.

7.5. Real Vulnerabilities in the Wild

In section 7.4, we have shown how Wildfire outperforms state-of-the-art techniques on programs that have a single user-interface, i.e. main function. We will now show that Wildfire can also find vulnerabilities in open-source libraries that have many possible entry points, i.e. APIs, that increase their attack surface. Unlike fuzzing and symbolic execution, Wildfire can analyze these libraries automatically, without the need for manually writing API drivers.

To demonstrate that Wildfire can effectively be used to test libraries without writing test-drivers, such as is the case with baseline tools, viz. AFL, KLEE, AFLFast and Munch, we picked three popular open-source libraries, listed below.

1. Libtiff 4.0.9\footnote{\url{http://www.simplesystems.org/libtiff/}} – A library used by application developers to process images of TIFF, and a few other, formats.
2. Libpng 1.6.35\footnote{\url{https://libpng.sourceforge.io/}} – A library used by application developers to process PNG images.
3. Libcurl 7.59.0\footnote{\url{https://curl.haxx.se/}} – A library for transferring data using various secure and non-secure transfer protocols.

Our goal with these case studies was to find out if we can reproduce the vulnerabilities reported in the past for them and if we can find any new ones.

For finding vulnerabilities, we filtered the list of all reported vulnerabilities (by Wildfire) to those where there was at least one API function in the chain of vulnerability. Table 4 lists all previously known vulnerable functions in the respective versions of Libtiff, Libpng and Libcurl. We obtained this list from NVD\footnote{\url{https://nvd.nist.gov/}} and then filtered them by the name of the library and the corresponding latest version. The second column of table 4 lists the known CVE identifier for the respective vulnerabilities. The last column shows whether Wildfire could find the same vulnerability in the given time-out. As we can see from table 4, all the known vulnerabilities in Libtiff and Libpng, and all but one vulnerabilities in Libcurl, could be found by Wildfire under the given time-limit.

We also found 23 new vulnerabilities in these three libraries that could be exploited through at-least one function in the respective libraries’ API. Table 5 lists the previously unknown vulnerabilities (of type “buffer errors”) in Libtiff, Libpng and Libcurl that can be exploited by an improper (but valid) use of their APIs.

\footnote{\url{http://www.simplesystems.org/libtiff/}}\footnote{\url{https://libpng.sourceforge.io/}}\footnote{\url{https://curl.haxx.se/}}\footnote{\url{https://nvd.nist.gov/}}
Table 4: Known Vulnerabilities in Libtiff 4.0.9, Libpng 1.6.35 and Libcurl 7.59.0

| Function | CVE Found by Wildfire |
|----------|-----------------------|
| TIFFSetupStrips | CVE-2017-17095 ✓ |
| PackBitsEncode | CVE-2017-17942 ✓ |
| TIFFPrintDirectory | CVE-2017-18013 ✓ |
| TIFFSetDirectory | CVE-2018-5784 ✓ |
| TIFFPrintDirectory | CVE-2018-7456 ✓ |
| LZWDecodeCompat | CVE-2018-8905 ✓ |
| TIFFWriteDirectorySec | CVE-2018-10963 ✓ |
| png_set_text_2 | CVE-2016-10087 ✓ |
| png_set_PLTE | CVE-2015-8126 ✓ |
| png_set_PLTE | CVE-2015-8126 ✓ |
| png_set_expand_palette | CVE-2013-6954 ✓ |
| png_free_data | CVE-2018-14048 ✓ |
| Curl_http_readwrite_headers | CVE-2018-1003030 ✓ |
| Curl_smtp_escape_eob | CVE-2018-0500 ✓ |
| Curl_auth_type3_message | CVE-2019-3822 ✗ |
| Curl_pp_readresp | CVE-2018-1003000 ✓ |

Table 5: New Vulnerabilities Discovered in Libtiff 4.0.9, Libpng 1.6.35 and Libcurl 7.59.0

| Vulnerable Function | Affected API |
|---------------------|--------------|
| TIFFFindField | TIFFGetFieldDefaulted |
| unixErrorHandler | TIFFFdOpen |
| TIFFRGBAImageOK | TIFFReadRGBAImage |
| TIFFSwabArrayOfShort | TIFFSwabArrayOfShort |
| TIFFSwabArrayOfLong | TIFFSwabArrayOfShort |
| TIFFWriteBufferSetup | TIFFWriteTile |
| png_set_fill_color | png_set_add_alpha |
| png_warning | png_set_compression_method |
| png_colorspace_set_chromaticities | png_set_cHRM |
| png_error | png_set_compression_buffer_size |
| png_set_keep_unknown_chunks | png_image_skip_unused_chunks |
| png_ice_check_header | png_set_ICC |
| png_tran_ok | png_set_alpha_mode |
| png_get_y_pixels_per_meter | png_get_y_pixels_per_inch |
| png_get_y_offset_microns | png_get_y_offset_inches |
| curl_easy_cleanup | curl_easy_cleanup |
| curl_easy_perform | curl_easy_perform |
| curl_getdate | curl_getdate |
| curl_mime_init | curl_mime_init |
| curl_slist_append | curl_slist_append |
| curl_slist_free_all | curl_slist_free_all |
| curl_easy_escape | curl_easy_escape |
| curl_easy_unescape | curl_easy_unescape |
7.6. Synthesis of the Results

7.6.1. RQ1 – Coverage

Several works in the past [32, 45, 22] have shown that the primary reason that state-of-the-art test-case generation techniques are unable to find many vulnerabilities is a lack of coverage in deeper parts of the code, often guarded by complex checks for malformed inputs. We, therefore, hypothesised that forcing higher coverage in programs would also lead to discovering previously unknown vulnerabilities. Compared to dynamic analysis techniques of symbolic execution and fuzzing, we showed in section 7.4 that Wildfire achieves higher line- and function-coverage. The reason for higher in-depth coverage was merely the under-constrained nature of the fuzzing stage, where isolated functions were analyzed directly. Symbolic execution and fuzzing tools could not cover as much of the source-code or functions because they had to overcome complex frontier nodes [35] to execute these functions.

RQ1 – Our results show that, for the selected benchmarks, Wildfire achieves higher in-depth line coverage and function coverage than basic and coverage-guided baseline tools.

7.6.2. RQ2 – Vulnerabilities

Our second research question was whether, as a result of higher coverage, Wildfire could also find more vulnerabilities in programs than the comparison baseline. Our conjecture was based on several previous works [15, 20, 32] that use symbolic execution at the level of isolated functions and found more vulnerabilities and increased coverage. In section 7.4, we found that, in fact, the number of vulnerabilities (including potential false-positives, as we will discuss soon) reported by Wildfire is always higher than state-of-the-art symbolic execution and fuzzing tools and comparable to the state-of-the-art compositional tool. Additionally, the number of vulnerabilities that could be exploited from the main function is also the same or higher.

Importantly, a compositional fuzzing framework can also help mitigate the problems induced by potential false-positives, as follows. In particular, not all reported vulnerabilities that cannot be triggered from an interface, such as main function, are false-positives. We provide three reasons for this claim here. 1. If a vulnerability can be shown to be exploitable through multiple caller-callee pairs (|chain| > 1), then it could potentially be true-positive and, hence, should be fixed. Anecdotal evidence of this is our observation on the motivating example of Bzip2 (section 3). The vulnerability in BZ2\_hbCreateDecodeTables was reported by Wildfire by, first, analyzing the isolated functions (section 5.4) and, then, determining feasibility of the vulnerabilities through compositional analysis (section 5.6). The reported chain, BZ2\_hbDecompress → BZ2\_decompress → BZ2\_hbCreateDecodeTables, with |chain| > 1, should indicate that the vulnerability should be fixed, even if the framework could not reproduce the feasible path from main function. Manually confirming all reported vulnerabilities with |chain| > 1 was not feasible in our
work, but sorting vulnerabilities by $|\text{chain}|$ should be the first step in bug-triage. A combination with targeted symbolic execution allows Wildfire also to report more chains ($\text{chain} \prec P^2$ in table 2) than from simply fuzzing the isolated functions and examining their stack-traces. Without targeted symbolic execution, as discussed in section 7.4, we would not have been able to find many critical vulnerabilities, some of which were reproducible through the top-level interface.

2. There may be many other factors [17], such as the degree of connectedness of a function [31] and the distance to an interface such as main function [33], that affect if a vulnerability may be exploited, even if an exploit from main could not be generated. 3. In practice, functions tend to be reused in unforeseen contexts and, hence, it may be advisable to fix vulnerabilities directly inside functions that may be reused.

RQ2 – Our results show that, for all but one selected benchmarks, Wildfire finds more vulnerabilities than basic, coverage-guided and compositional baseline tools. It also finds more, or the same number of, true-positives as the baseline tools.

7.6.3. RQ3 – Testing Libraries

Our final research question was whether Wildfire could help in effectively testing libraries to find vulnerabilities, without the time-consuming process of writing drivers. By applying our framework to three popular open-source libraries, Libtiff, Libpng and Libcurl, we showed in section 7.5 that all, but one, of the known vulnerabilities, could have been found by Wildfire. We were also able to find new vulnerabilities and report them to their development teams. This is an essential contribution of our research because open-source libraries with public APIs are often used as daemon or microservices on remote servers accepting input through standard protocols, such as HTTP. If a malicious user was to send malformed input to the API to trigger the discovered vulnerabilities, they could cause a denial-of-service resulting in a substantial monetary and functional loss. Wildfire, by reporting all chains of potential vulnerabilities directly affecting the API functions, would discover and help in mitigating these vulnerabilities at the earliest. For the vulnerabilities that could not be confirmed to be feasible from the API, i.e. potential false-positives, we argue for them in the same manner as earlier, viz. with reports containing chains of vulnerable functions, it makes it easier for developers and testers to triage the reported bugs.

RQ3 – Our results show that, for the selected open-source libraries, Wildfire can effectively find vulnerabilities in them without writing specialised drivers for automatically testing them.

8. Limitations

*Pointer Analysis.* Currently, support for a few kinds of pointers in Wildfire is insufficient. Particularly, if a function parameter list contains at least one pa-
rameter of double- or more pointers (such as array-of-arrays), then the function will not be isolated and fuzzed. The same is true if there is at least one parameter of function-pointer type. In case of pointers to structures which may, themselves, contain members of pointer data-types, Wildfire attempts to allocate memory for them (using malloc) and extract values for them from the function arguments, as described in section 5.2.2. However, if there are no explicit checks on pointers inside structures, then a crash resulting from their access will be, correctly, reported.

**Global Variables.** Another limitation of Wildfire is that it does not take into account, and hence fuzz, the values of global variables that might affect the internal states of isolated functions. However, as is also true for past works in compositional analysis [15, 21, 32], when including all possible global variables in the argument extraction procedure, the search space for possible executions explodes intractably.

Due to the above reasons, and possibly more, our results may not generalise to other kinds of C programs that may functionally or structurally differ from our evaluation set. However, we have taken care to, firstly, not exclude any programs by design in our study and, secondly, include programs varying from medium- to large-scale, in terms of the number of high-level source-code lines and functions. We applied these selection criteria to, both, open-source programs with a main entry point and open-source libraries that are popularly used by many third-party applications.

9. Conclusion

In this paper, we presented Wildfire, a compositional analysis framework based on a novel combination of fuzzing and symbolic execution. Wildfire can find more real, and potentially exploitable, vulnerabilities in open-source programs and libraries than state-of-the-art fuzzing, symbolic execution, in only 10% as much time in most cases, accounting for parallelisation of analysis. Compared to the only other compositional analysis tool at our disposal, Wildfire was able to find more vulnerabilities and almost the same number of true-positives in the same amount of time, also taking into account parallelisation. Wildfire deals with false-positives by precisely reporting the chains of functions through which a vulnerability can be exploited. This can be, as shown by our case studies, particularly useful and practical for testing libraries where there may be multiple entry-points to a program. In the future, we would like to implement summarisation of vulnerabilities by path-constraints rather than concrete argument values. We also wish to extend Wildfire by combining with symbolic execution to adaptively switch between the two techniques when one saturates in isolated functions. By using heuristics from existing bug reports, we would, in the future, include an automated bug-triage plugin for vulnerabilities discovered by Wildfire.
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