Multiple Targets Directed Greybox Fuzzing

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Abstract—Directed greybox fuzzing (DGF) can quickly discover or reproduce bugs in programs by seeking to reach a program location or explore some locations in order. However, due to their static stage division and coarse-grained energy scheduling, prior DGF tools perform poorly when facing multiple target locations (targets for short). In this paper, we present multiple targets directed greybox fuzzing which aims to reach multiple programs locations in a fuzzing campaign. Specifically, we propose a novel strategy to adaptively coordinate exploration and exploitation stages, and a novel energy scheduling strategy by considering more relations between seeds and target locations. We implement our approaches in a tool called LeoFuzz and evaluate it on crash reproduction, true positives verification, and vulnerability exposure in real-world programs. Experimental results show that LeoFuzz outperforms six state-of-the-art fuzzers, i.e., QYSM, AFLGo, Lolly, Berry, Beacon and WindRanger in terms of effectiveness and efficiency. Moreover, LeoFuzz has detected 23 new vulnerabilities in real-world programs, and 12 of them have been assigned CVE IDs.

Index Terms—Crash reproduction, directed greybox fuzzing, true positives verification, vulnerability exposure.

I. INTRODUCTION

CONTEXT. Currently, fuzzing is one of the most effective and practical techniques to discover bugs or vulnerabilities automatically. By constantly mutating seeds initially provided, fuzzers generate lots of new inputs and report those that cause the program under test (PUT) failure or crash [12]. A greybox fuzzer such as AFL [13] uses program feedback like branch coverage to boost the efficiency of finding bugs. However, its consideration to achieve maximum code coverage may waste a lot of resources in some bug independent code.

By contrast, directed greybox fuzzers, e.g., AFLGo [14], Lolly [15], Berry [16], spend most of the time budget in reaching target program locations (targets for short), e.g., problematic changes, critical APIs or potential bugs, and thus are more suitable for patch testing and crash reproduction etc. For example, AFLGo uses harmonic distance between a seed and targets to reach the targets fast. Lolly exploits target statement sequences to trigger bugs which are resulted from the sequential execution of multiple statements. Berry uses concolic execution to enhance the directedness when reaching deep targets along some complex paths.

It is reasonable and meaningful for DGF to seek to reach multiple targets. There are often multiple bugs in real-world programs due to their large-scale and complexity. To demonstrate the situation, we randomly selected nine widely-used programs in the real world and counted the bugs or vulnerabilities in them. As shown in Table I, at least three CVEs were discovered in each of them. Therefore, software developers or testers often deal with lots of potential bugs, for example those reported by static analyzers, in different situations, such as crash reproduction or regression testing.

To expose or verify multiple (e.g., $n$) bugs in a program via directed greybox fuzzing, one way is to run in parallel $n$ fuzzing instances, each of which is given a single target to trigger a single bug; another way is to run a directed greybox fuzzing instance with $n$ targets to trigger $n$ bugs, e.g., AFLGo, Lolly and Berry. Though both methods are complementary, in this paper, our goal is to improve the effectiveness and efficiency of the second way on real-world programs.

Problems. Although DGF is efficient by spending more resources to explore the code towards the target locations, prior DGF tools [14], [15], [16] perform poorly when facing multiple target locations due to their coarse-grained energy scheduling and static stage division.

Problem 1. An energy scheduling strategy is usually designed in the Fuzzers to control the number of seed mutations. In DGF, the scheduling strategy gradually adds (reduces) energy to seeds closer to (far away) target locations, which helps trigger multiple targets faster. For example, AFLGo gives more energy to a seed with a smaller harmonic distance to all targets, though this strategy makes AFLGo ignore the local optima.

TABLE I
A REAL-WORLD PROGRAM USUALLY CONTAINS MULTIPLE BUGS

| Program  | Version | #Bugs |
|----------|---------|-------|
| cxxshf   | 2.25    | 6     |
| httpd    | 2.4.46  | 7     |
| jasper   | 2.0.14  | 14    |
| jasper   | 2.0.12  | 15    |
| libming  | 0.4.8   | 70    |
| objdump  | 2.15    | 6     |
| readelf  | 2.28    | 8     |
| sqlite   | 3.32.0  | 10    |
| tcpdump  | 4.9.3   | 26    |
| tiff2pdf | 4.09    | 3     |
| tiff2pdf | 4.08    | 4     |

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To cover multiple targets, pursuing a global optimal scheduling for all targets would ignore local optimal scheduling for some targets, as AFLGo does, while seeking an optimal scheduling for a single target would make other targets difficult to be reached, as Lolly and Berry do. It is a challenge to design a suitable energy scheduling for reaching as many targets as possible within a time limit.

Problem 2. DGF works in two stages, i.e., exploration and exploitation. In the exploration stage, the fuzzer aims to obtain more code coverage through seeds mutation and execution, thereby obtaining more run-time information. In exploitation stage, the fuzzer mutates and executes seeds to get seeds closer to the target locations. For instance, AFLGo begins with the exploration stage first and randomly mutates the initial seeds to generate many new inputs, in order to increase code coverage. It then enters exploitation stage to generate more new inputs which are increasingly closer to the targets. However, the time to enter exploitation stage is specified statically. For example, AFLGo specifies 20 hours for exploration and 4 hours for exploitation. This static switching strategy ignores the dynamic runtime information and may decrease the performance of AFLGo.

Less exploration would provide less coverage information for exploitation, making it difficult to generate high-quality directed seeds in exploration stage. However, overmuch exploration would cost many resources and delay the exploitation, resulting in loss of directedness. Therefore, it is also a challenge to coordinate exploration and exploitation stages in order to balance the coverage and directedness in DGF.

Proposal. To solve the above problems, we present multiple targets directed greybox fuzzing to efficiently cover multiple programs locations in a single fuzzing campaign. Specifically, we propose a novel energy scheduling strategy that considers multiple relations between a seed and target sequences (MES for short) and a novel approach to adaptively coordinate exploration and exploitation stages (CEE for short) based on two queues.

As for energy scheduling, unlike AFLGo, which considers the harmonic distance between a seed and multiple targets in energy scheduling, and also unlike Lolly, which uses seed’s target sequence coverage as the feature of energy scheduling, for a seed \( s \) and multiple target sequences, MES first selects the target sequence \( ts \) which has the highest coverage over \( s \’ \) execution trace, and then considers three relations between the seed and target sequences for energy scheduling, namely \( s \’ \) sequence coverage (\( seqCov \)), \( ts \’ \) priority (\( priority \)) and global maximum coverage (\( gMaxCov \)). Specifically, MES assigns more energy to seeds with high \( seqCov \), high \( priority \), low \( gMaxCov \), and vice versa. In this way, MES enables our fuzzer to reach as many targets as possible. Our key insight here is that considering both the global metrics (i.e., priority and global maximum coverage of a target sequence) and local metrics (i.e., a seed’s sequence coverage over a target sequence) will benefit to solve the first problem, i.e., prior fuzzers failed to pursue global optima and local optima during covering multiple targets.

CEE uses a queue to store seeds which help to reach the targets (directed seeds for short) and another queue to store seeds that increase the code coverage (coverage seeds for short). If the proportion of the coverage seeds in the total seeds is too high (e.g., exceeds a threshold rate) when exploring, our fuzzer switches to exploitation stage. If code coverage information is insufficient (e.g., the fuzzer does not generate new directed seeds during a long period) when exploiting, our fuzzer turns to the exploration stage. Moreover, CEE adjusts the threshold rate dynamically by recording the duration time and the number of generated directed seeds in each exploitation stage, in order to coordinate the exploration and exploitation stage adaptively.

Evaluation. We implemented the above techniques in a tool named LeoFuzz and conducted extensive experiments with seven real-world programs. Evaluation results demonstrate that LeoFuzz is effective and efficient on crash reproduction, true positives verification, and vulnerability discovery, compared to six state-of-the-art fuzzers i.e., QSYM, AFLGo, Lolly, Berry, Beacon and WindRanger. Contrary to intuition, running a fuzzer with multiple targets in a single fuzzing campaign is more efficient than running multiple fuzzer instances in parallel with a target per instance. In addition, LeoFuzz found in three real-world programs 23 new vulnerabilities and 12 of which are assigned CVE IDs.

Contributions. The main contributions of this paper are as follows:

- An adaptive stage coordination approach which steers the fuzzer to switch between exploration stage and exploitation stage dynamically;
- A novel energy scheduling strategy which considers more relations between a seed and targets and hence enables to reach multiple targets efficiently;
- A tool named LeoFuzz can expose and verify vulnerabilities in real-world programs. We make LeoFuzz publicly available\(^1\) to foster further research in the area;
- Extensive evaluation results show that LeoFuzz outperforms six state-of-the-art fuzzers, i.e., QSYM, AFLGo, Lolly, Berry, Beacon and WindRanger, on crash reproduction and true positives verification. Moreover, LeoFuzz found in three real-world programs 23 new vulnerabilities and 12 of which are assigned CVE IDs.

The rest of this article is structured as follows. Our motivation is described in Section II. We present LeoFuzz’s overall design in Section III, static analysis in Section IV, dynamic analysis in Section V, and its implementation in Section VI. Section VII presents the evaluation of LeoFuzz. We discuss the related work in Section IX, threats to validity in Section VIII and conclude in Section X.

II. Motivation

In this section, we use an example to discuss two limitations of the existing DGF tools and introduce our approach.

Fig. 1 shows a part of the inter-procedural control flow graph (ICFG) of objdump program (V2.31). Each node in the figure indicates a basic block, whose details are shown in Table II. Two shadowed nodes, i.e., \( m \) and \( p \), refer to an out-of-memory vulnerability and an integer overflow vulnerability respectively.

\(^1\)https://github.com/hongliangliang/leofuzz
Problem 1: unsuitable energy scheduling hinders covering multiple targets. Existing DGF tools use two energy scheduling strategies. AFLGo adapts Dijkstra algorithm to schedule seeds, and Lolly or Berry exploits target sequence coverage in energy scheduling. When testing the objdump program, AFLGo had an execution trace for each of three seeds, i.e., a-c-e-i-q-m, a-b-d-k-o and a-b-d-f-g-j-k-p, respectively. It calculates the harmonic distance \( d_a \), we label it aside the node in Fig. 1) between each node in these paths to two targets. For example, the harmonic distance of node \( a \) is \( d_a = 2/(1/5 + 1/4) = 40/9 \), where 5 and 4 is the length of the shortest path from \( a \) to target \( m \) and \( p \) respectively, and 2 represents two targets that \( a \) can reach. So the global distances of three seeds are \( d_{aceiqm} = (40/9 + 4 + 3 + 2 + 1)/5 = 2.89 \), \( d_{abdko} = (40/9 + 3 + 2 + 1)/4 = 2.61 \), \( d_{abdfgjkp} = (40/9 + 3 + 2 + 4 + 3 + 2 + 1)/7 = 2.78 \), respectively. AFLGo prefers to select the seed with the smallest global distance, i.e., a-b-d-k-o here, though it is not reasonable as the seed covers none of two targets. In fact, the other two seeds, i.e., a-c-e-i-q-m and a-b-d-f-g-j-k-p, can reach the target \( m \) and \( p \) respectively, each of which deserves be chosen more likely. Therefore, AFLGo would ignore the local optimum when seeking global optimal scheduling, thus reducing the directedness of fuzzing.

By contrast, Lolly or Berry may fall into an easy local optimum and thus never explore other deep targets. For example, if the paths going through the target \( m \) are more difficult to explore (e.g., due to complex conditions) than those going through the target \( p \), the target sequence coverage of a seed close to \( m \) would increase more slowly than that of another seed close to \( p \). So both tools would generate a large number of seeds exploring the right branch of Fig. 1, and only a few seeds covering the left branch of Fig. 1. They would continue to explore the right branch of Fig. 1 even after reaching the target \( p \). As a result, it is difficult for them to schedule a seed close to the target \( m \).

Problem 2: Improper Exploration-Exploitation Division. Existing DGF tools switch between exploration and exploitation stage in three ways. The first one uses the seed selection strategy without considering the exploration-exploitation switchover, like Lolly [15]. The generated coverage seeds or directed seeds are placed at the end of a queue for sequential scheduling. This method is simple but may take a long time to mutate those directed seeds at (or near) the rear of the queue, which slows down the reaching of targets. The second is the static division strategy used by AFLGo [14] and RDFuzz [24], which gives each stage a fixed period. This strategy is not flexible and does not consider the runtime information at all. The third is the exploitation-first strategy used in Berry [16]. It divides the seed queue into three priority levels, and directed seeds have higher priority than coverage seeds. This strategy doesn’t work well when the fuzzer has insufficient code coverage information, hence causing a lower quality of the generated seeds.

Our approach. To solve the above problems, we propose and implement two techniques in LeoFuzz. 1) a fine-grained energy scheduling strategy, which considers more relations between seeds and targets, e.g., target sequence priority, target sequence coverage and global maximum coverage. Our strategy can avoid ignoring the local optimum like AFLGo and avoid falling into an easy local optimum like Lolly or Berry. For instance, when seeds always have a higher coverage with the target sequence of \( p \) than that of \( m \), we can know that target \( m \) is more difficult to reach than target \( p \). Thus the global maximum coverage of the target \( m \) is lower. Therefore, more energy is given to seeds with high sequence coverage of target \( m \) (i.e., a-c-e-i-1). In this way, LeoFuzz has more chances to explore the left branch of Fig. 1, thus more likely to reach target \( m \). 2) an adaptive exploration and exploitation coordination approach, which is based on two queues storing directed seeds and coverage seeds respectively. LeoFuzz coordinates exploration and exploitation stage flexibly according to the ratio of seeds in two queues.

LeoFuzz also uses a concolic executor to solve difficult constraints, such as magic number, which enables LeoFuzz to reach targets quickly. In addition, LeoFuzz combines call graph (CG) and control flow graph (CFG) to increase the length of each target sequence, thus further improving LeoFuzz’s guidance on reaching targets.

III. APPROACH

The architecture of LeoFuzz is shown in Fig. 2, which includes two phases, i.e., static analysis and dynamic analysis. In the static analysis phase, the graph extractor extracts a CG and a set of CFG from the program under test (PUT). Then the target sequence generator maps the statements in targets to basic blocks of the graphs and generates for each target a target sequence, which contains necessary basic blocks along the paths to the target. Finally, the PUT is instrumented for collecting runtime...
information, such as code coverage and execution traces, and the instrumented binary is sent to the executor.

In the dynamic analysis phase, the fuzzer takes the initial seeds and the instrumented binary as inputs. First, the stage coordinator judges the stage of the fuzzer (exploration stage or exploitation stage). According to the stage, the seed selector then obtains a seed from the corresponding seeds queue, i.e., coverage seeds queue (CQ for short) or directed seeds queue (DQ for short). After the mutator mutates the seed, the generated input is fed to the executor. The input is stored into the crash queue if it crashes the PUT, or into DQ if it increases the target sequence coverage, or into CQ if it increases code coverage, otherwise discarded. The fuzzer communicates with the concolic executor by sharing two seed queues. The concolic executor helps LeoFuzz focus on the paths going through the targets and explore more branches thus obtaining better code coverage. The concolic executor obtains seeds from two queues and stores its generated directed inputs or coverage inputs into the corresponding queue.

IV. STATIC ANALYSIS

A. Generating Target Sequences

Given a target, a target sequence is composed of a set of nodes, and each node is a necessary basic block which exists on all paths from the entry function (e.g., main) to the target. To make the fuzzer have better guidance, LeoFuzz combines CG and CFG of the PUT to enhance the target sequences, unlike Lolly and Berry, which only use CFG to generate target sequences.

As shown in Algorithm 1, we generate the target sequence for a target based on Dominator Tree\(^2\) [36]. It takes a program \(P\) and a target \(T\) as inputs, and outputs the target sequence \(TS\) which is initially empty. The algorithm first obtains CG from \(P\) and converts it to the dominator tree \((\text{domCg})\) (lines 2-3). Then we get CFG and convert it to the dominator tree \((\text{domCfg})\) (lines 4-5). We then get the target function name \(\text{funName}\) (lines 6-7). Finally, we get the necessary nodes from \(\text{domCf}g\) and \(\text{domCg}\) respectively, and add them to \(TS\) (lines 7-9).

Algorithm 1: Target Sequence Generation

| Input: Program \(P\), Target \(T\) |
|-----------------------------------|
| **Output:** Target Sequence \(TS\) |

1: \(TS = \emptyset\);
2: \(\text{cg} = \text{getCG}(P)\);
3: \(\text{domCg} = \text{CG-to-Dom}(	ext{cg})\);
4: \(\text{cfg} = \text{getCFG}(P, T)\);
5: \(\text{domCfg} = \text{CFG-to-Dom}(	ext{cfg})\);
6: \(\text{funName} = \text{getFunName}(P, T)\);
7: \(\text{seq1} = \text{getNesNodesByCFG}(\text{domCfg}, T)\);
8: \(\text{seq2} = \text{getNesNodesByCG}(\text{domCg}, \text{funName})\);
9: \(TS = TS \cup \text{seq2} \cup \text{seq1}\);

We use an example to illustrate the algorithm, as shown in Fig. 3. The figure shows the CG of a program \(P\) and the CFG of function \(G\) which contains a target \(g\), as well as the dominating trees \(\text{domCg}\) and \(\text{domCfg}\). The blue nodes in the figure represent the necessary nodes to reach the target \(g\). Using Algorithm 1, we can know that main1-A1-entry-a-f-g is the target sequence of the target \(g\), where main1 and A1 represents the entry node of main and A function, respectively.

B. Static Instrumentation

Like Lolly, LeoFuzz instruments the basic blocks each of which contains at least a target statement, and uses a shared memory to sequentially record identifiers of the blocks following the order in which they are executed (i.e., execution trace). As a result, the fuzzer can collect the code coverage information and execution traces related to targets during execution. These runtime information assists LeoFuzz in energy scheduling and exploration-exploitation coordination.

V. DYNAMIC ANALYSIS

During the dynamic analysis stage, the fuzzer and the concolic executor independently executes the program under test while they help each other by sharing the coverage seed queue (CQ) and the directed seed queue (DQ).
Algorithm 2: Multiple Targets Directed Grey-box Fuzzing.

Input: Instrumented Binary $P$, Target Sequence Set $TSS$, Coverage seed queue $CQ$, Directed Seed queue $DQ$.
Output: Crash seeds $CS$.

1: $sof = 0$; $epoch = 0$; $dsc = 0$; $csc = 0$; $ndc = 0$; $cdsc = 0$;
2: repeat
3: $sof = stageCoord(sof)$;
4: if $sof == 0$ then
5: $s = getNextSeed(CQ)$;
6: else
7: $s = getNextSeed(DQ)$;
8: end if
9: $p = assignEnergy(s)$;
10: for $i$ from 1 to $p$ do
11: $s’ = mutate(s’)$;
12: execute($P, s’$);
13: if $s’$ crashes $P$ then
14: add $s’$ to CS.
15: else
16: $tseqCov = isIncreaseTSeqCov(s’, TSS)$;
17: $codeCov = isIncreaseCodeCov(s’)$$csc$;
18: if $tseqCov$ then
19: add $s’$ to DQ;
20: $dsc++; cdsc++; ndc = 0$; continue;
21: end if
22: if $codeCov$ then
23: add $s’$ to CQ;
24: $csc++; ndc++; continue;
25: end if
26: $ndc++;
27: end if
28: end for
29: until timeout or abort

A. Fuzzer

The fuzzer in LeoFuzz works like other DGF tools though we enhance it with two novel techniques. We propose a novel approach to adaptively coordinate exploration and exploitation stages (CEE for short) based on two queues and a novel energy scheduling strategy that considers more relations between seeds and targets (MES for short).

The fuzzer’s workflow is shown in Algorithm 2. Its inputs are the instrumented binary $P$, coverage seed queue $CQ$, directed seed queue $DQ$ and target sequence set $TSS$, and the output is a set of crash seeds $CS$. Table III describes the meaning of each symbol/variable used in Algorithms 2 and 3.

After initialization, the fuzzer decides its stage using CEE Algorithm 3 and accordingly selects a seed $s$ from $CQ$ or $DQ$ respectively (lines 3-8). It then assigns energy $p$ to the seed using MES strategy. In the energy loop, the fuzzer generates a new input $s’$ via mutation, and executes $P$ with $s’$. If $s’$ causes the program crash, increases code coverage or target sequence coverage, the fuzzer stores it in CS, CQ or DQ respectively (lines 13-25). Note that if $s’$ increase both code coverage and target sequence coverage, we store it in $DQ$ since directed seeds are usually less than coverage seeds.

1) Exploration-Exploitation Coordination: CEE mechanism is shown in Algorithm 3. The fuzzer starts in the exploration stage initially and will switch to exploitation stage when the ratio of coverage seeds ($csc$) in total seeds is greater than a dynamic threshold $rate$, which means that fuzzer has adequate code coverage information, so we set $sof$ as exploitation stage, and updates the related data, e.g., $ndc, cdsc, epoch$ (lines 1-7).

In exploitation stage, we record related runtime information, e.g., $cdsc$ and $ndc$, as shown in Algorithm 2. The fuzzer will switch to exploration stage when $ndc$ exceeds a threshold $th$, which indicates that the fuzzer’s exploitation ability is weak now. Therefore we set $sof$ as exploration stage in order to explore more code paths, and update the coefficient $rate$ (lines 8-16). The threshold $th$ is calculated by the values of $ndc$ in last two epochs and $epoch$ (line 9). Because the probability of finding a new directed seed decreases gradually during fuzzing, we increase $th$ at each epoch to keep the fuzzer in exploitation stage longer.
The *rate* is used to decide when the fuzzer switches from the exploration stage to the exploitation stage, so we update its value by using run-time information in the current exploitation stage (e.g., *cdsc*) only before the fuzzer will leave for the exploration stage. Obviously, the greater the *rate* is, the longer the fuzzer stays in exploration, and vice versa. To balance the fuzzer’s code coverage and directed exploitation, we use function *updateRate* to adjust *rate* according to epoch and *cdsc*, as follows:

\[
rate^* = rate - \gamma \left( \tanh \left( \frac{cdsc}{\sqrt{t}} + \sqrt{\text{epoch}} \right) - \delta \right)
\]

(1)

where *rate* indicates the new value of *rate* for use in next exploration stage, \(\tanh()\) is a hyperbolic function, \(t\) represents the time duration (seconds) of current exploitation stage. (Note: the upper and lower bound of *rate* is set to 1 and 0, respectively. \(\gamma\) and \(\delta\) are used to control *rate* varying within this range.)

Specifically, the larger \(\frac{cdsc}{\sqrt{t}}\) is, which means that more directed seeds are produced in exploitation stage and that current code coverage is helpful in reaching targets, the less time the fuzzer would use to reach targets and should switch to exploitation stage as soon as possible. As such, we reduce *rate* to make the fuzzer enter exploitation stage fast. On the contrary, the smaller \(\frac{cdsc}{\sqrt{t}}\) is, which indicates that current code coverage does not help reach targets, the more exploration time is needed to get more coverage information, therefore we increase *rate* to keep the fuzzer exploring longer. In addition, the probability of finding a new directed seed decreases gradually during fuzzing, resulting in a smaller \(\frac{cdsc}{\sqrt{t}}\) and a greater *rate* over time. Therefore, we use the parameter *epoch* to offset this effect so that *rate* changes reasonably.

2) Seed Energy Scheduling for Multiple Targets: To balance the energy scheduling for multiple targets, we propose a novel energy scheduling strategy (MES for short) that considers more relations between seeds and targets.

Specifically, for a seed \(s\) and multiple targets, LeoFuzz generates all target sequences (e.g., \(N\) in total) at the static analysis phase (Section IV) and obtains the seed’s execution trace during fuzzing. We consider three relations between the seed and target sequences as follows.

- The priority of a target sequence \(TS_i\), which indicates \(TS_i\)’s similarity with other sequences and is computed at static analysis phase as follows:

\[
priority_i = \sum_{j=1}^{N} \frac{\text{LCS}(TS_i, TS_j)}{\text{Max}(TS_i, TS_j)} \geq \epsilon \quad ?1:0 \quad , j \neq i
\]

(2)

where LCS() indicates the length of the longest common subsequence of two sequences, Max() returns the maximum length of two sequences. The higher the priority, the greater the chance that the fuzzer can reach multiple targets by mutating \(s\), so \(s\) should be assigned more energy.

- The global maximum coverage \(g^{MaxCov}\) of a target sequence \(TS_i\). It refers to the maximum coverage of any execution trace in the past over the target sequence, which approximates \(TS_i\)’s difficulty to cover and is updated during dynamic analysis. (In fact, the \(g^{MaxCov}\) used for the next seed energy scheduling is obtained by calculating the maximum value of the \(\text{seqCov}\) of the current seed and the current \(g^{MaxCov}\).) The less \(g^{MaxCov}_i\) is, \(TS_i\) is more difficult to be covered, the target corresponding to \(TS_i\) is more difficult to reach, and thus the seed should be assigned more energy.

- The seed’s sequence coverage \(\text{seqCov}\) over a target sequence \(\langle TS_i \rangle\). It measures the similarity between the seed’s execution trace (ET) and \(TS_i\), and is calculated during dynamic analysis as follows:

\[
\text{seqCov}_i = \frac{\text{LCS}(ET, TS_i)}{\text{length}(TS_i)}
\]

where LCS() gets the length of the longest common subsequence between \(s^*\) execution trace and \(TS_i\). The greater the \(\text{seqCov}_i\), the more likely that the fuzzer will cover \(TS_i\) by mutating \(s\), so \(s\) should be assigned more energy.

For a seed and multiple targets, MES selects the target sequence with the maximum value of \(\text{seqCov}\) as the seed’s outstanding target sequence \((OTS)\) for short, and considers OTS’ priority, \(g^{MaxCov}\) and the seed’s \(\text{seqCov}\) over OTS when scheduling energy for the seed. In this way, LeoFuzz can provide a fine-grained energy scheduling and thus effectively improve the ability of DGF to cover multiple targets.

Below we show how to calculate these values by using an example. Given three target sequences, \(TS_1: a\text{-}b\text{-}c\text{-}d\text{-}e\text{-}f\text{-}g\), \(TS_2: a\text{-}b\text{-}c\text{-}g\text{-}h\), \(TS_3: a\text{-}g\text{-}i\text{-}k\). We first calculate the priority of each target sequence as follows. LCS(\(TS_1, TS_2\) and LCS(\(TS_1, TS_3\)) is 3 and 1 respectively, Max(\(TS_1, TS_2\) and Max(\(TS_1, TS_3\) are 6, so the priority of \(TS_1\) is 1 according to (2). Similarly the priority of \(TS_2\) and \(TS_3\) is 1 and 0 respectively. Suppose that seed \(s^*\) execution trace (ET) is a\text{-}b\text{-}c\text{-}g\text{-}k\text{-}m\text{-}d\text{-}a\text{-}c, we can get LCS(\(ET, TS_1\) = 3, and \(s^*\) sequence coverage over \(TS_1\) is 3/6 = 0.5 according to (2). Similarly that of \(s\) over \(TS_2, TS_3\) is 0.8 and 0.25 respectively. Therefore, \(s^*\) sequence coverage is 0.8, and \(s^*\) OTS is \(TS_2\). Assuming that three seeds in total were executed in the past and their coverage with \(TS_2\) is 0.3, 0.5 and 0.4 respectively, then the global maximum coverage of \(TS_2\) is 0.5.

It is arduous to judge which target is difficult to reach when the fuzzer has insufficient code coverage, especially in initial executions. Therefore, we won’t consider global maximum coverage of the target sequence in energy scheduling until the fuzzer has sufficient code coverage. For example, when the number of target sequences whose global maximum coverage is greater than or equal to a threshold (\(\beta\)) exceeds half of total sequences, the fuzzer likely has covered shallow (or easy) targets, it is reasonable to consider those deep (or difficult) targets. Therefore, those seeds corresponding to these targets will be allocated less energy and other targets have more opportunities to be explored.

\[3\text{If there are multiple ones, the first is used.}\]
We use a comprehensive factor (CF) to represent the above relations:

\[
CF = \begin{cases} 
\frac{1}{2} (seq Cov + priority/N), & \text{if } \sum_{j=1}^{N} (gMaxCov_j \geq \beta: 1:0) < \frac{1}{2} N \\
\frac{1}{2} (seq Cov + priority/N + (1 - gMaxCov)), & \text{if } \sum_{j=1}^{N} (gMaxCov_j \geq \beta: 1:0) \geq \frac{1}{2} N 
\end{cases}
\]

(4)

where N is the number of total sequences.

AFLGo uses an energy scheduling scheme based on simulated annealing in the greybox fuzzing. Different from the traditional random walk algorithm which may be trapped in a local optimum, the simulated annealing algorithm accepts a solution which is worse than the current one with a certain probability, so it can jump out of the local optimum and reach the global optimum. This probability gradually decreases as the control parameter temperature decreases.

Like AFLGo, LeoFuzz also applies simulated annealing to our energy scheduling for a global optimum and uses the same coefficient values as AFLGo in the following equations. For multiple targets directed fuzzing, an optimal solution is a test case that can achieve the maximum CF. In our method, the temperature T with an initial value \( T_0 = 1 \) is exponentially cooled.

\[
T = T_0 \times \alpha^k
\]

(5)

where, \( \alpha \) is a constant which meets \( 0.8 \leq \alpha \leq 0.99 \), and k is the temperature cycle. The threshold of \( T_k \) is set to 0.05. The fuzzer will not accept worse solutions when the temperature is lower than \( T_k \). Specifically, if \( T_k > 0.05 \), LeoFuzz randomly mutates the existing seeds to generate many new inputs. Otherwise, it generates more new inputs from seeds with higher CF. In this case, the simulated annealing process is similar to the traditional gradient descent algorithm.

Since a common limitation of fuzzing is the time budget, we use time t to adjust the temperature cycle k:

\[
k/k_x = t/t_x
\]

(6)

where \( k_x \) and \( t_x \) are the temperature cycle and the time respectively when temperature drops to \( T_k \). So we use k to establish the relationship between time t and temperature T:

\[
T_k = 0.05 = \alpha^{k_x}
\]

(7)

\[
T = \alpha^k = \alpha^{t/t_x \times \log(0.05)/\log(\alpha)} = 20^{-t/t_x}
\]

(8)

Given a seed s, multiple targets, and their comprehensive factor (CF), we define the capability of s to cover the given multiple targets as:

\[
Cap = CF \times (1 - T) + 0.5 \times T
\]

(9)

At the beginning of fuzzing, the initial value of temperature T is 1, which means that Cap is independent of CF. As time goes on, the temperature T gradually decreases and CF becomes increasingly important.

To combine our MES strategy with the existing seed energy schedule algorithm of a fuzzer (e.g., AFL), LeoFuzz integrates the capability of covering multiple targets (Cap) into the energy calculation formula. LeoFuzz calculates the integrated energy for a seed as:

\[
Menergy = energy \times 2.4^{(Cap^{-0.2} \times 10)}
\]

(10)

where energy is the original energy given by AFL and Menergy is the energy given by LeoFuzz which integrates MES strategy in the original fuzzer.

B. Concolic Executor

The fuzzer leverages a random mutation to generate test inputs without considering the context of the PUT and thus it has difficulty to reach deep targets and find deep errors along complex paths [25, 26, 32, 33]. Therefore, we combine the fuzzer with the concolic executor to solve this problem. The concolic executor continuously obtains seeds from two seed queues, executes them, and generates new inputs, which are then put into CQ or DQ if they bring new code coverage or new target sequence coverage. To generate directed seeds as quickly as possible so that LeoFuzz can reach the targets faster, the concolic executor prefers to acquire seeds from DQ first and then seeds from CQ if there are no available directed seeds.

VI. IMPLEMENTATION

Static analysis: We wrote an LLVM pass which builds call graph (CG) for the program under test and control flow graph (CFG) for each of its functions. The dominator tree is constructed for each CFG and CG by NetworkX, and the necessary nodes are calculated to obtain the target sequence. We modified the AFL’s instrumentation pass which writes the IDs of basic blocks in a target sequence into the shared memory, in order to record the target sequence’s execution trace.

Dynamic analysis: We implemented our exploration-exploitation coordination strategy and energy scheduling strategy in AFL. In addition, we modified the concolic executor in QSYM to leverage guidance from the directed seeds, and hence LeoFuzz can reach the targets faster.

VII. EVALUATION

A. Experiment Setup

We conducted all experiments on a virtual machine with an Intel(R) Xeon(R) Gold 6126 CPU, 128 GB RAM and Ubuntu 18.04 (64 b) as operating system. To evaluate the effectiveness and efficiency of LeoFuzz, we compare it with six state-of-the-art fuzzers, AFLGo, Lolly, Berry, QSYM, Beacon and
WindRanger, and utilize an additional CPU core for concolic executor in hybrid fuzzers, i.e., Berry, QSYM and LeoFuzz. We evaluated them with the same programs under test, initial input corpus, target locations and time budget (12 hours). Since Beacon cannot support multiple targets, we ran it and compared it with LeoFuzz in experiments with single target. Note that Hawkeye [19], RDFuzz [24] and CAFL [31] are not publicly available, so LeoFuzz doesn’t compare with them. We attempted to compare LeoFuzz with ParmeSan [22] but we could not replicate its experiments successfully even after we asked its authors for help.

We leverage seven real-world programs shown in Table IV for all experiments except clearly stated, because these programs are widely used, extensively evaluated by fuzzing tools in both academia [17], [19], [34] and industry [35], and found vulnerable due to multiple bugs. For these programs, we collected 31 vulnerabilities and corresponding arguments from CVE database or their official sites and took each vulnerability’s crash site as a target in experiments, i.e., A unique target location corresponds to a unique vulnerability. Furthermore, we repeated all experiments 10 times and used the average values. In the experiments, we aim to answer the following questions:

**RQ1** How does LeoFuzz perform when it is given a single target each time?

**RQ2** Is LeoFuzz effective and efficient in crash reproduction?

**RQ3** How does running LeoFuzz with multiple targets compared to running multiple LeoFuzz instances with one target per instance?

**RQ4** Is LeoFuzz efficient in terms of true positives verification?

**RQ5** Is LeoFuzz effective to discover vulnerabilities in real-world software?

**RQ6** How do four main design decisions contribute to LeoFuzz?

### B. Crash Reproduction

Software programs may crash due to potential bugs or vulnerabilities. A crash report usually contains memory dumps or call stacks of the program. Based on it, developers need to generate test cases that trigger the crash, i.e., reproduce the crash. Directed fuzzing technique is demonstrated effective on crash reproduction [14], [15], [16].

Using 31 vulnerabilities from seven real-world programs shown in Table IV, we evaluate LeoFuzz’s ability on crash reproduction. We conduct experiments using two settings: 1) we run LeoFuzz with a single target (i.e., RQ1), in this case, we name it LeoFuzz× for convenience, and 2) we run LeoFuzz with multiple targets (RQ2), comparing to baseline tools, respectively. Then we compare the difference between two settings of LeoFuzz (i.e., RQ3).

1) **RQ1: Performance of LeoFuzz When Given a Single Target:** The experimental results for RQ1 are shown in Table V. The first column is the program under test. The second and third columns are the number of targets that are given to the program under test and the second column lists the fuzzing tools. The fourth column is the number of bugs reproduced by each tool to trigger a unique vulnerability. Furthermore, we repeated all experiments 10 times and used the average values. In the experiments, we aim to answer the following questions:

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TABLE V
RESULTS OF LeoFuzz AND Baseline Tools WHEN GIVEN A SINGLE TARGET. UAF=USE-AFTER-FREE, IO=INTEGER OVERFLOW, BOF=BUFFER OVERFLOW, SOF=STACK OVERFLOW, NP=NULL POINT Exception, ML=MEMORY LEAK, AE=ARITHMETIC ERROR, OR=out-of-Bounds READ, IR=INVALID MEMORY READ

| Program | CVE-ID  | Type | QSYM | AFLGo | Lolly | Berry | Beacon | LeoFuzz* |
|---------|---------|------|------|-------|-------|-------|--------|---------|
|         | TTE     | Factor | TTE | Factor | TTE | Factor | TTE | Factor | TTE | Factor |
| xxxfilt | 2016-4487 | 0.54s | 2.32 | 2.36 | 3.12s | 2.56 | 1.86 | 2.50s | 2.27 |
|         | 2016-4489 | 0.53s | 2.04 | 1.16 | 3.21s | 1.76 | 1.29 | 2.51s | 1.50 |
|         | 2016-4490 | 0.50s | 1.56 | 1.56 | 4.9s  | 1.53 | 1.31 | 34s  | 1.06 |
|         | 2016-4491 | 0.50s | 1.69 | 2.16 | 1h43m | 2.08 | 1h19m | 1h26m | 1.73 |
|         | 2016-4492 | 0.50s | 1.17 | 4.41s | 2.23 | 5m17s | 2.52 | 5m52s | 2.32 |

| objdump | 2018-17985 | SOF | — | 3.43 | 3.43 | 1h17m | 2.95 | 7h41m | 2.21 |
|         | 2018-20671 | IO  | 1.89 | 9h44m | 1.54 | —     | 1.89 | 7h27m | 1.18 |
|         | 2019-9138 | SOF | — | 4.11 | 4.11 | —     | 4.11 | 4.11  | 2h59m | 1.01 |
|         | 2019-9070 | SOF | — | 5.14 | 6h2m | 2.60 | 6h53m | 2.97 | 4h47m | 2.06 |

| readeLF | 2017-7209 | 0.40m | 5.35 | 5.35 | 1h56m | 2.21 | —     | 13.64 | 54m28s |
|         | 2019-14444 | 0.40m | 3.80 | 3.80 | 3h51m | 3.21 | 3h12m | 2.67 | 10.00 | 1h12m |

| tiff2pdf | 2018-15209 | 0.40m | 4.11 | 4.11 | —     | 11.80 | 4h83m | 4.64 | —     | 11.80 |
|         | 2018-16335 | 0.40m | 7.04 | 7.04 | 5h23m | 3.17 | 4h13m | 2.48 | —     | 7.06 |

| dwg2dx | 2019-9770 | 0.40m | 1.90 | 1.90 | 9h11m | 2.15 | 8h19m | 1.95 | —     | 2.81 |
|         | 2019-9771 | 0.40m | 17.37 | 17.37 | 3h15m | 2.81 | 7h49s | 2.22 | 28m18s | 2.25 |
|         | 2019-9772 | 0.40m | 19.73 | 19.73 | 2h57m | 4.85 | 2h15m | 3.81 | —     | 19.73 |
|         | 2019-9773 | 0.40m | 1.82 | 1.82 | 9h17m | 2.13 | 8h13m | 2.04 | —     | 2.75 |
|         | 2019-9774 | 0.40m | 32.17 | 32.17 | 10m10s | 1.91 | 7m26s | 1.40 | 7m2s | 1.32 |
|         | 2019-9775 | 0.40m | 2.32 | 2.32 | 5h1m | 8.02 | 3h32m | 5.65 | 5h45m | 9.18 |
|         | 2019-9776 | 0.40m | 15.47 | 15.47 | 1h53m | 2.43 | 2h12m | 2.84 | 1h45m | 2.21 |
|         | 2019-9777 | 0.40m | 1.46 | 1.46 | 47s  | 1.68 | 35s  | 1.18 | 31s  | 1.11 |
|         | 2019-9778 | 0.40m | 1.22 | 1.22 | 42m57s | 1.57 | 47m31s | 1.73 | 39m32s | 1.44 |
|         | 2019-9779 | 0.40m | 12.33 | 12.33 | 59m47m | 1.60 | 53m24s | 1.41 | 43m44s | 1.17 |

| unzipcat-mem | 2017-5974 | 0.40m | 4.31 | 4.31 | 7h36m | 2.73 | 8h30m | 3.09 | 7h42m | 2.77 |
|              | 2017-5975 | 0.40m | 18.32 | 18.32 | 1h16m | 1.93 | 1h30m | 1.60 | —     | 18.32 |
|              | 2017-5977 | 0.40m | 11.67 | 11.67 | 38m50m | 1.91 | 41m22s | 2.04 | 26m49s | 1.32 |
|              | 2017-5978 | 0.40m | 10.09 | 10.09 | 33m26s | 1.34 | 37m43s | 1.39 | 31m4s | 1.14 |
|              | 2017-5980 | 0.40m | 6.44 | 6.44 | 1h23m | 3.02 | 1h8m | 2.47 | 57m54s | 2.11 |
|              | 0.40m | 2.49 | 2.49 | 6m17s | 1.89 | 6m9s | 1.85 | 6m11s | 1.86 |
|              | 0.40m | 3.01 | 3.01 | 10m29s | 1.00 | 30m12s | 1.99 | 31m54s | 2.10 |

3) **RQ3: One LeoFuzz With Multiple Targets Versus Multiple LeoFuzz With a Target Per Instance:** As shown in the previous sections, both LeoFuzz and LeoFuzz* are effective in crash reproduction. Then a question arises naturally; running LeoFuzz with multiple targets or running multiple LeoFuzz instances with one target per instance, which one is more efficient? We explore the question in this section and the experimental results are shown in Table VII. The third and fourth column is the sum and the longest of TTE spent by each LeoFuzz* instance to trigger a given vulnerability respectively. The fifth column measures the vulnerabilities triggered by LeoFuzz, and the sixth column is the TTE spent by LeoFuzz to trigger all vulnerabilities in each program.

As shown in Table VII, both one LeoFuzz instance and multiple LeoFuzz* instances can trigger all vulnerabilities, however, the time cost of LeoFuzz is less than the total time and even the longest time spent by each LeoFuzz* instance. For example, LeoFuzz spent 56m11s when triggering both CVE-2017-7209 and CVE-2019-14444 in readelf program, while LeoFuzz* took 1h12m when triggering CVE-2019-14444 only (see Table V). The efficiency of LeoFuzz may benefit from the fact that real-world programs often have multiple bugs which are usually dependent or related, e.g., caused by the same bad programming practices. In fact, we observed that the call stack in crash dump caused by CVE-2017-7209 has a large overlap with that caused by CVE-2019-14444, in other words, the paths to reach both vulnerabilities go through much same functions, which helps LeoFuzz trigger both of them fast.

We further carried on experiments to evaluate LeoFuzz with more targets and experimental results are shown in Table VIII. The 2nd column means the CVEs listed in Table V. The 6th one is the potential bugs reported by Clang static analyzer. The targets in the 4th column are selected randomly from the 6th one. TTE refers to the minimum time spent by LeoFuzz after reaching all targets. LeoFuzz’s performance is slightly reduced when the number of targets increases, but it still consumes less time than those of baseline tools (refer to Table VI). The reason behind may be that the energy scheduling would cost more time with the increase of targets, while those targets which are unreachable are eliminated effectively by our techniques.

C. **RQ4: Efficiency on True Positives Verification**

Developers and testers usually apply static analysis tools to discover bugs or vulnerabilities in software before release. However, static analysis tools often have high false positive,
TABLE VI  
RESULTS OF LEOFUZZ AND BASELINE TOOLS WHEN GIVEN MULTIPLE TARGETS

| Prog.   | Tool  | Tgt. | Rep. | Add. | TTE   | Factor | $A_{12}$ |
|---------|-------|------|------|------|-------|--------|----------|
|        | QSYM  | 5    | 5    | 1    | 1.02m | 1.79   | 0.59     |
|        | AFLGo | 5    | 5    | 1    | 1.05m | 2.46   | 0.54     |
|        | Lolly | 5    | 5    | 1    | 1.37m | 2.09   | 0.62     |
|        | Berry | 5    | 5    | 2    | 1.17m | 1.75   | 0.55     |
|        | WindRanger | 5 | 5    | 2    | 39m50s | 0.86   | 0.41     |
|        | LeoFuzz | 5 | 5    | 3    | 46m22s | —      | —        |

TABLE VII  
LEOFUZZ VS MULTIPLE LEOFUZZ+ INSTANCES

| Program  | Tgt. | LeoFuzz+ Total TTE | LeoFuzz+ Longest TTE | Rep | LeoFuzz TTE |
|----------|------|--------------------|----------------------|-----|-------------|
| cxxfilt  | 5    | 55m23s             | 49m36s               | 5   | 46m22s     |
| objdump  | 4    | 4h28m               | 6h48m                | 4   | 4h28m      |
| readeff  | 2    | 2h4m                | 1h17m                | 2   | 1h17m      |
| tiff2pdf | 6    | 6h99m               | 1h17m                | 6   | 1h17m      |
| dwg2dxf  | 5    | 54m28s             | 25m42s               | 5   | 25m42s     |
| unzzipc-atmem | 6 | 6h94m | 24m11s | 6 | 24m11s |
| mjs      | 2    | 2h4m                | 1h17m                | 2   | 1h17m      |

and thus require a lot of manual efforts to verify their analysis results. Due to its directed execution feature, the DGF technique has been used for automatic verification of bugs [14], [15], [16]. Moreover, Lolly and Berry outperformed over AFLGo due to their sequence coverage approach [15], [16].

We evaluated LeoFuzz’s ability on true positive verification and compared it with QSYM, AFLGo, Lolly, Berry and WindRanger. We use the same subject program, i.e., Libming 0.4.8 [43], as AFLGo, Lolly and Berry. In addition, we run the Clang Static Analyzer [37] on the subject program and use its analysis results as targets, i.e., the code locations of potential bugs. In the experiments, the analysis results of the Clang analyzer are not intentionally filtered and therefore may contain false positives and infeasible paths. In order to evaluate the efficiency of LeoFuzz and the baseline tools, we guide them with the above targets to trigger CVE vulnerabilities of Libming and compare their time cost. The CVE vulnerabilities are listed in the first column of Table IX.

Table IX presents the experimental results. The second to the eleven column is the mean of TTE and factor of QSYM, AFLGo, Lolly, Berry and WindRanger in ten runs, respectively. In particular, if a tool fails to trigger a vulnerability in a run within the time limit, its TTE is uniformly recorded as the time budget (i.e., 12 hours). The last column is the mean TTE of LeoFuzz.

As shown in Table IX, LeoFuzz and the baseline tools successfully generated inputs that can trigger the vulnerabilities, while LeoFuzz is 2.71× faster than QSYM, 2.70× than AFLGo, 2.02× than Lolly, 1.78× than Berry and 2.68× than WindRanger, respectively. Experimental results show that LeoFuzz is effective in true positives verification and more efficient than baseline tools.

D. RQ5: Effectiveness on Vulnerabilities Exposure

To evaluate LeoFuzz’s ability exposing bugs or vulnerabilities in real-world programs, we tested three widely used software with their latest versions, i.e., cxxfilt 2.36, SWFTools a9d5082 [44] and libredwg 0.12.4.4608 [40]. Cxxfilt is a tool in Binutils, which decodes low-level names into user-level names to be human readable. SWFTools is a collection of utilities for working with Adobe Flash files. LibreDWG is a free C library to read and write DWG files. The targets in this experiment come from the results of Clang static analyzer [37] or the patches of the corresponding program under test, and LeoFuzz aims to explore towards the potentially buggy code.

As a result, LeoFuzz found 23 previously unreported vulnerabilities, 12 of which are assigned CVE IDs and others have been confirmed by the corresponding developers. Under

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TABLE IX
RESULTS ON TRUE POSITIVE VERIFICATION

| CVE-ID  | QSYM | AFLGo | Lolly | Berry | WindRanger | LeoFuzz |
|---------|------|-------|-------|-------|------------|---------|
| TTE     | Factor | TTE   | Factor | TTE   | Factor     | TTE     |
| 2018-9132 | 6h17m | 2.38  | 6h35m | 2.30  | 4h57m | 1.55  | 3h57m | 1.50  | 7h19m | 2.75  | 2h39m |
| 2018-9009 | 2h46m | 2.41  | 4h37m | 4.30  | 2h13m | 1.93  | 2h17m | 1.99  | 1h53m | 1.64  | 1h9m  |
| 2018-8807 | 18m34s| 2.37  | 25m19s| 3.22  | 18m59s| 2.42  | 14m32s| 1.85  | 18m59s| 2.42  | 7m52s |
| 2018-7877 | 2h49m | 2.68  | 3h11m | 3.03  | 2h21m | 2.24  | 2h9m  | 2.05  | 3h37n | 3.44  | 1h3m  |
| 2018-7876 | 4h47m | 3.83  | 2h35m | 2.07  | 2h13m | 1.77  | 2h22m | 1.89  | 1h59m | 1.59  | 1h15m |
| 2018-7875 | 3h2m  | 2.98  | 2h59m | 2.93  | 2h10m | 2.13  | 1h53m | 1.85  | 4h1m  | 3.95  | 1h1m  |
| 2018-7873 | 2h57m | 2.98  | 2h49m | 2.85  | 2h2m  | 2.05  | 1h37m | 1.63  | 2h45m | 2.78  | 59m21s|
| 2018-7872 | 5h21m | 3.19  | 4h47m | 2.79  | 3h49m | 2.42  | 3h11m | 2.05  | 6h18m | 2.50  | 1h43m |
| 2018-7870 | 2h49m | 2.35  | 3h1m  | 2.51  | 2h11m | 1.82  | 1h46m | 1.47  | 3h8m  | 2.61  | 1m12m |
| 2018-7868 | 5h21m | 2.94  | 5h7m  | 2.82  | 3h23m | 1.86  | 3h45m | 2.06  | 5h51m | 3.22  | 1h49m |
| 2018-7867 | 2h59m | 3.11  | 2h55m | 3.04  | 2h7m  | 2.21  | 2h17m | 1.86  | 2h48m | 2.92  | 5m32s |
| 2018-6359 | 19m52s| 2.51  | 23m28s| 2.97  | 17m12s| 2.18  | 14m36s| 1.85  | 24m37s| 3.11  | 7m55s |
| 2018-6315 | 3m13s| 1.27  | 2m58s | 1.17  | 3m55s | 1.55  | 2m59s | 1.18  | 3m78s | 3.01  | 2m32s |
| 2018-20591| 5h18m | 4.61  | 4h32m | 4.23  | 2h11m | 1.90  | 2h17m | 1.99  | 3h14m | 2.81  | 1h9m  |
| 2018-20249| 7h49m | 4.38  | 4h56m | 2.76  | 3h37m | 2.03  | 3h19m | 1.86  | 6h21m | 3.56  | 1h47m |
| 2018-20247| 6h17m | 2.37  | 6h9m  | 2.35  | 4h0m  | 1.53  | 3h31m | 1.34  | 7h26m | 2.84  | 2h37m |
| 2018-13251| 10m5s | 1.69  | 8m5s  | 1.36  | 12m34s| 2.11 | 9m32s | 1.60  | 11m3s | 1.86  | 6m57m |
| 2018-11226| 3h11m | 2.94  | 2h59m | 2.75  | 1h59m | 1.83  | 1h45m | 1.62  | 2h58m | 3.05  | 1h5m  |
| 2018-11225| 5m45s | 1.36  | 5m28s | 1.30  | 6m7s  | 1.45  | 4m34s | 0.96  | 5m48s | 1.38  | 4m13s |
| 2018-11017| 55m55s| 4.82  | 39m25s| 3.40  | 39m14s| 3.38  | 33m32s| 2.89  | 25m18s| 2.18  | 11m42s|

TABLE X
UNREPORTED VULNERABILITIES FOUND BY LEOFUZZ

| Program | Type  | Reported as                        |
|---------|-------|------------------------------------|
| cxxfilt | SOF   | CVE-2021-3330                      |
|         | SOF   | ubuntu bug-1927070                 |
|         |        |                                    |
| SWFTools| BOF   | CVE-2021-42195                     |
|         | NP    | CVE-2021-42196                     |
|         | ML    | CVE-2021-42197                     |
|         | NP    | CVE-2021-42198                     |
|         | BOF   | CVE-2021-42199                     |
|         | NP    | CVE-2021-42200                     |
|         | BOF   | CVE-2021-42201                     |
|         | NP    | CVE-2021-42202                     |
|         | UAF   | CVE-2021-42203                     |
|         | BOF   | CVE-2021-42204                     |
|         |        |                                    |
| libredwg| BOF   | issues-484                         |
|         | NP    | issues-485                         |
|         | UAF   | issues-486                         |
|         | BOF   | issues-487                         |
|         | BOF   | issues-489                         |
|         | UAF   | issues-490                         |
|         | BF    | issues-491                         |
|         | AE    | issues-492                         |
|         | DF    | issues-493                         |
|         | SBOF  | CVE-2022-33034                     |

the same experimental setup, other fuzzers can find part of 23 new bugs found by LeoFuzz. Specifically, QSYM, AFLGo, Lolly, Berry and WindRanger found 14, 11, 10, 17 and 14 bugs respectively. Table X presents the subject program, the buggy method, the type and CVE/Bug ID of each vulnerability, where BOF=buffer overflow, SOF=stack overflow, NP=null point exception, MAF=memory allocation failure, UAF=use-after-free, ML=memory leak, BF=bad free, AE=assert error, DF=double free, SBOF=stack buffer overflow. Eight of twelve CVEs are assigned high severity score. Below we discuss one of them in detail to highlight the ability of LeoFuzz. LeoFuzz found a use-after-free vulnerability in SWFTools package, i.e., CVE-2021-42203, which involves different functions in multiple files. As shown in Figs. 4 and 5, the program uses a pointer t of TAG type at the line swftext.c:498, and frees it at the line rfxswf.c:1234. When testing the program, LeoFuzz successfully explored a path where function swf_ReadTag is called.
E. RQ6: Contributions of Four Design Decisions

To evaluate the contributions of four main design decisions in LeoFuzz, i.e., target sequence enhancement, exploration-exploitation coordination, fine-grained energy scheduling strategy and concolic execution, we disabled each technique and compiled four variants of LeoFuzz and named them LeoFuzz-tes, LeoFuzz-cee, LeoFuzz-mes and LeoFuzz-dse respectively. We ran LeoFuzz and its four variants against those programs in Table IV and the results are shown in Table XI. The TTE columns indicate the mean value of TTEs spent by LeoFuzz-tes, LeoFuzz-cee, LeoFuzz-mes and LeoFuzz-dse to trigger all CVEs in each subject program, and the factor columns reflect the TTE’s ratio between four variants and LeoFuzz. Moreover, we drew diagrams showing LeoFuzz’s success of exploration and exploitation over time, as shown in Fig. 6.

We have two findings: 1) Each technique contributes to LeoFuzz as the performance of each variant is weaker than LeoFuzz; 2) The contribution of MES is better than that of CEE and that of target sequence enhancement, which are better than that of concolic execution. It is reasonable because MES considers both the relations between a seed and targets and the relations within multiple target sequences.

VIII. Threats to Validity

Internal validity: The main internal threat is the randomness of fuzzing. We conducted the experiments multiple times for fairness, and as initial seeds might influence the outcomes in the fuzzing experiments, we used the same seeds to LeoFuzz as inputs to each baseline in all experiments. The second internal threat comes from the configurable options in LeoFuzz, e.g., two parameters in (1) and (2), which are currently set based on our preliminary experiments. Though the current results are promising, we believe fine-tuning them may improve the experiment results but it is not the key technique here. Therefore, we leave it as future work.

External validity: Although our experimental results may vary to other programs, to mitigate this threat, we chose 31 vulnerabilities in seven real-world programs that have been frequently evaluated in the existing fuzzers. These programs also have diverse functionalities as well as different program sizes. Moreover, these chosen vulnerabilities come from different types (9 in total) and thus the difficulty of triggering them varies.

Construct validity: We compare different configurations of LeoFuzz according to the main techniques proposed in this paper, so we can understand that any effect on the results is due to their differences, and can also verify that the proposed strategies are all effective.

IX. Related Work

A. Coverage-Based Greybox Fuzzing

Greybox fuzzing is scalable and practical in finding bugs or vulnerabilities in software. AFL [13] uses lightweight compile-time instrumentation, coverage feedback and genetic algorithm to generate test cases that can trigger vulnerabilities in programs. Compared with blackbox fuzzing [29] and whitebox fuzzing [27], [28], greybox fuzzing has higher efficiency and effectiveness [13], [35].

To improve the exploration ability of greybox fuzzing, Vuzzer [26] uses dynamic data-flow analysis in greybox fuzzing
to maximize coverage and explore deeper paths. Angora [32] solves path constraints by gradient descent algorithm to improve the coverage of branches. REDQUEEN [18] leverages a lightweight input-to-state correspondence mechanism as an alternative to data-flow analysis and symbolic execution. GREYONE [21] exploits a data flow-sensitive fuzzing scheme since fuzzing based on traditional data flow analysis is inaccurate and slow. DeepFuzzer [48] first uses symbolic execution to generate qualified initial seeds that can help pass complex checks, then applies a statistical seed selection algorithm to balance mutation frequencies among different seeds. Its hybrid mutation strategy aims to balance global exploration and deep search. To refine the seed scheduling of greybox fuzzing, AFLFast [25] shows that most test cases execute high-frequency paths, so AFLFast assigns more energy to those seeds which can pass through the low-frequency paths. EcoFuzz [30] proposes a variant of the Adversarial MultiArmed Bandit (VAMAB) model to model scheduling problems and balances exploration stage and exploitation stage for reasonable seed selection, while LeoFuzz coordinates two stages adaptively to balance the fuzzer’s code coverage and directedness. AFLsmart [47] leverages a high-level structural representation of the seed file and new mutation operators to generate new files, and introduces a validity-based power schedule to spend more time generating files that are more likely to pass the parsing stage of the program.

Unlike the above efforts that aim to improve the performance of coverage-based greybox fuzzing, LeoFuzz is a target-oriented directed greybox fuzzer that aims to trigger multiple target sites in a single instance. PAFL [46] extends existing fuzzing optimizations of single mode to industrial parallel mode by dividing tasks and synchronizing guiding information. It improves the fuzzing efficiency by running more instances of multiple fuzzers and is complementary to our approach.

### B. Directed Greybox Fuzzing

AFLGo [14] is the first directed greybox fuzzer (DGF), its simulated annealing-based power schedule gradually assigns more energy to seeds that are closer to the target sites while reduces energy for seeds that are far away. Based on AFLGo, Hawkeye [19] supports indirect calls and adjusts its seed prioritization, power scheduling and mutation strategies adaptively to reach the target sites rapidly. However, Hawkeye has similar problems with AFLGo when dealing with multiple targets. As discussed in Section II, their unsuitable energy schedule may ignore local optimal solutions and hinder covering multiple targets efficiently. Moreover, their strategy of coordinating exploration-exploitation stages is static and inflexible. Also based on AFLGo, RDfuzz [24] prioritizes a seed by combining its input-distance to the target sites and its trace’s frequency and uses a static intertwined schedule to perform exploration and exploitation in turn. By contrast, LeoFuzz dynamically coordinates exploration and exploitation stages according to the ratio of directed seeds and coverage seeds.

Some directed fuzzers exploit a sequence-based guided approach. Lolly [15] is the first sequence directed greybox fuzzer. For a given set of target statement sequences, Lolly aims to generate inputs that can reach the statements in each sequence in order. Berry [16] uses the target program’s CFGs to extend the given target sequence to improve the directedness of fuzzing. UAFL [23] focuses on UAF vulnerability and thus takes use-after-free sequence to guide its fuzzer. Lolly, Berry and UAFL consider the execution order of targets, while LeoFuzz further takes into account three kinds of relation between seeds and targets, i.e., seed’s target sequence coverage, priority and global maximum coverage of each target sequence.

Several directed fuzzers leverage the output of sanitizers to guide fuzzing. SAVIOR [20] uses the output of UBSan as target sites, and calculates a seed’s energy according to the new branches that the seed meets, the target sites on these branches and the difficulty of solving these branches’ constraints. Parmesan [22] leverages the errors or warnings reported by multiple sanitizers as target sites and then guides the fuzzers by the distance from a seed to a target. LeoFuzz can also use the results from sanitizers as targets though it does not depend on sanitizers.

Several directed fuzzers use data flow analysis or data conditions. CAFL [31] aims to satisfy a sequence of constraints and prioritizes the seeds that better satisfy those in order. It defines a constraint as a single target site and optionally a number of data conditions. If multiple constraints are specified, they must be satisfied in the specified order. CAFL assumes that the target sites are dependent to each other while LeoFuzz support multiple independent target sites. CAFL requires the additional information sources, i.e., crash dumps from memory error detectors and changelogs from patches, to generate the constraints. Moreover, CAFL was evaluated with up to 2 targets and cannot cover bugs that require three or more constraints, while LeoFuzz triggered ten bugs in dwg2dxf within four hours in our evaluation. Considering that each basic block isn’t equally important in seed distance calculation, WindRanger [49] uses the deviation basic blocks (DBBs) and their data flow information for seed distance calculation, mutation, seed prioritization and energy scheduling. It dynamically switches between the exploration and exploitation stage according to the execution status of DBBs. Beacon [50] leverages a provable path pruning method to improve the efficiency of DGF. It identifies infeasible paths via control flow reachability and path condition satisfiability, instruments those related statements, and prunes these paths during fuzzing. By contrast, LeoFuzz combines concolic execution and fuzzing by sharing two types of seeds, and hence can solve the path constraint for a seed and mutate the validated inputs satisfying the path condition. Overall, these methods are orthogonal to LeoFuzz and can be integrated with LeoFuzz for better performance.

### C. Hybrid Techniques

Combining fuzzing and symbolic execution is an active area of research [16],[52],[53],[54]. To find deeper bugs, Driller [53] integrates fuzzing and selective concolic execution in a complementary manner, i.e., it uses fuzzing to exercise modules of an application, and concolic execution to generate inputs which satisfy the complex checks separating the modules. Aiming at differential software analysis, HyDiff [54] extends greybox
fuzzing and shadow symbolic execution, and applies search heuristics like output and cost difference to guide the exploration and maximize the execution divergence. Like Driller, LeoFuzz leverages concolic execution to generate inputs for conditions that the fuzzier cannot satisfy though the contribution of concolic execution is less than other three design decisions, as described in RQ6.

X. CONCLUSION

We present a multiple targets directed greybox fuzzing approach, which leverages a novel strategy to adaptively coordinate exploration and exploitation stages, and a novel energy scheduling strategy that considers more relations between seeds and targets, i.e., target sequence coverage, target sequence priority and global maximum coverage of target sequence. Our approach also uses concolic execution to help the fuzzers explore complex branches in programs. We implement our approach in LeoFuzz and evaluate it on crash reproduction, true positives verification, and vulnerability exposure in seven real-world programs. Experimental results show that LeoFuzz outperforms six state-of-the-art tools, i.e., QYSM, AFLGo, Lolly, Berry, Beacon and WindRanger.

As future work, we will combine parallel programming with LeoFuzz to improve its performance further. We are also planning to combine LeoFuzz with QEMU emulator to discover vulnerabilities in embedded devices.

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