Precise Attack Synthesis for Smart Contracts

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Abstract—Smart contracts are programs running on top of blockchain platforms. They interact with each other through well-defined interfaces to perform financial transactions in a distributed system with no trusted third parties. But these interfaces also provide a favorable setting for attackers, who can exploit security vulnerabilities in smart contracts to achieve financial gain.

This paper presents SMARTSCOPY, a system for automatic synthesis of adversarial contracts that identify and exploit vulnerabilities in a victim smart contract. Our tool explores the space of attack programs based on the Application Binary Interface (ABI) specification of a victim smart contract in the Ethereum ecosystem. To make the synthesis tractable, we introduce summary-based symbolic evaluation, which significantly reduces the number of instructions that our synthesizer needs to evaluate symbolically, without compromising the precision of the vulnerability query. Building on the summary-based symbolic evaluation, SMARTSCOPY further introduces a novel approach for partitioning the synthesis search space for parallel exploration, as well as a lightweight deduction technique that can prune infeasible candidates earlier. We encoded common vulnerabilities of smart contracts in our query language, and evaluated SMARTSCOPY on the entire data set from etherscan with >25K smart contracts. Our experiments demonstrate the benefits of summary-based symbolic evaluation and show that SMARTSCOPY outperforms two state-of-the-art smart contracts analyzers, YENTE and CONTRACTFUZZER, in terms of running time, precision, and soundness. Furthermore, running on recent popular smart contracts, SMARTSCOPY uncovers 20 vulnerable smart contracts that contain the recent BatchOverflow vulnerability and cannot be precisely detected by existing tools.

I. INTRODUCTION

Smart contracts are programs running on top of blockchain platforms such as Bitcoin [11] and Ethereum [2]. They have been receiving much attention due to the capability to perform effective financial transactions in a distributed system without the intervention of trusted third parties (e.g., banks). A smart contract is written in a high-level programming language (e.g., Solidity [3]), and it is typically comprised of a unique address, persistent storage holding a certain amount of cryptocurrency (i.e., Ether in Ethereum), and a set of functions that manipulate the persistent storage to fulfill credible transactions without trusted parties. For contract-to-contract interaction, some functions are public and callable by other contracts. Thanks to the expressiveness afforded by the high-level programming languages and the security guarantees from the underlying consensus protocol, smart contracts have shown many attractive use cases, and their number has skyrocketed, with over 45 million instances covering financial products, online gaming, real estate [5], shipping, and logistics [6].

Because all smart contracts deployed on a blockchain are freely accessible through their public methods, any functional bugs or vulnerabilities inside the contracts can lead to disastrous losses, as demonstrated by recent attacks [7, 8, 9, 10]. For instance, the code in Figure 1 illustrates a reentrancy vulnerability exploited in the notorious DAO attack [7]. When the victim program issues a money transaction (line 9 in Figure 1) to the attacker, it implicitly triggers the attacker’s callback method (line 3 in Figure 1), which invokes the victim’s method again to make another transaction without updating the victim’s balance. The DAO attack led to a financial loss of $150M in 2016. To make things worse, smart contracts are immutable—once they are deployed, fixing their bugs is extremely difficult due to the design of the consensus protocol.

Improving robustness of smart contracts is thus a pressing practical problem. It is also an active area of research, with several contract analysis tools [11, 12, 13, 14, 15, 16] developed in the past few years. However, these tools either soundly overapproximate the execution of smart contracts and report warnings [12, 14] that cannot be exploited in reality, or they precisely enumerate [16, 13, 11] concrete traces of smart contracts, so cannot scale to analyze large programs.

This paper presents SMARTSCOPY, a tool that uses program synthesis to automatically generate adversarial smart contracts.
(i.e., attack programs), which exploit common vulnerabilities in victim contracts. To use our tool, a security analyst expresses a target vulnerability query (e.g., the reentrancy vulnerability from the DAO attack) as a declarative specification. Then, SMARTSCOPY synthesizes an attack program that exploits the victim’s public interface to satisfy the vulnerability query. Given this problem, a naive approach is to enumerate all possible candidate programs and then symbolically evaluate each of them to check if it satisfies the query. While precise, the naive approach fails to scale to realistic contracts. To tackle this challenge, we employ a novel summary-based symbolic evaluation, which enables SMARTSCOPY to both find real attacks and scale to large programs.

Fig. 2 shows an overview of our approach. Given the public methods provided by the Application Binary Interface (ABI) of a smart contract, our system first symbolically evaluates each method and generates a summary that soundly records the method’s side-effects on the storage as well as other global state of the Blockchain. Even with the summaries, the search space is still too large for brute-force enumeration. To address this issue, we partition the search space by case splitting on the range of symbolic variables, which allows us to simultaneously explore multiple attack programs using an SMT-based symbolic evaluation engine [17]. SMARTSCOPY further reduces the search space by pruning infeasible candidates early, using their abstract semantics. After that, our tool symbolically evaluates each remaining candidate to check if any of them satisfies the vulnerability query. If so, the candidate is returned as a potential exploit.

We have evaluated SMARTSCOPY on the entire data set (>25K) from etherscan [4] and shown that our tool is expressive, efficient, and effective. SMARTSCOPY’s query specification language is expressive in that it is rich enough to encode common vulnerabilities found in the literature (such as the Reentrancy attack [7], Time manipulation [18], and malicious access control [19]), Security Best Practices [19], as well as the recent batchOverflow Bug [20] (CVE-201810299), which allows the attacker to create an arbitrary amount of cryptocurrency. SMARTSCOPY is efficient: on average it takes only 8 seconds to analyze a smart contract from etherscan, which is an order of magnitude faster than OYENTE [11] and two orders of magnitude faster than CONTRACTFUZZER [13]. SMARTSCOPY is also effective in that it significantly outperforms two state-of-the-art smart contracts analyzers, namely, OYENTE and CONTRACTFUZZER, in terms of false positive and false negative rates. Furthermore, running on recent popular smart contracts, SMARTSCOPY uncovers 20 vulnerable contracts that contain the BatchOverflow vulnerability and cannot be precisely detected by existing tools.

In summary, this paper makes the following key contributions:

- We formalize the problem of exploit generation as a program synthesis problem and provide a way of expressing common vulnerabilities in smart contracts as declarative specifications (Section IV-B).
- We propose a summary-based symbolic evaluation technique that significantly reduces the number of instructions that SMARTSCOPY has to execute (Section V).
- We develop an efficient attack synthesizer based on the summary-based symbolic evaluation, which incorporates a novel combination of search space partitioning, parallel symbolic execution, and early pruning based on the abstract semantics of candidate programs (Section VI-B).
- We perform a systematic evaluation of SMARTSCOPY on the entire data set from etherscan. Our experiments demonstrate the substantial benefits of our technique and show that SMARTSCOPY outperforms two state-of-the-art smart contracts analyzers in terms of running time, precision, and soundness (Section VII).

II. BACKGROUND

This section briefly reviews the background on blockchains and smart contracts.

A. Blockchain and Ethereum

Blockchain, invented by Satoshi Nakamoto in 2008, is a distributed public ledger that stores transactions between different parties. A blockchain is comprised of a growing list of blocks, each of which contains the hash of the previous block, a timestamp when the block is appended, and transaction value. Due to the decentralized consensus protocol, each block is inherently resistant to modification once it is created.

While Satoshi’s original blockchain proposes a peer to peer e-cash system that offers secure transactions, the Ethereum [21] blockchain provides a more powerful distributed computing platform that can execute custom code in the form of smart contracts. In addition to the crypto tokens (i.e., Ether) that are transferred among parties during a transaction, Ethereum also implements a gas scheme (explained in Section II-C) to incentivize miners who perform the computationally expensive creation of new blocks.
A. Smart Contract Vulnerabilities

Smart contracts are programs that are stored and executed on the blockchain. They are created through the transaction system on the blockchain and are immutable once deployed. Each smart contract is associated with a unique 256-bit address; a private persistent storage; a certain amount of cryptocurrency, denoted by balance (i.e., Ether in Ethereum) held by the contract; and a piece of executable code that fulfills complex computations to manipulate the storage and balance. The code is typically written in a high-level Turing-complete programming language such as Serpent [22], Vyper [23], and Solidity [3], and then compiled to the Ethereum Virtual Machine (EVM) bytecode [21], a low-level stack-based language. For instance, Figure 4a shows a sample smart contract written in the Solidity programming language [3].

C. ABI and Transactions

In the Ethereum ecosystem, Smart Contracts communicate with each other using the Contract Application Binary Interface (ABI), which defines the signatures of public functions provided by the hosted contract. While ABI offers a flexible mechanism for communication, it also creates an attack surface for exploits that use the ABI of a given smart contract. We will elaborate on this in the following section. For instance, Figure 4c shows the ABI for the smart contract in Figure 4a.

All interactions between smart contracts are fulfilled by transactions. Table I shows a sample transaction obtained from Etherscan. Here, the important fields are From, To, Value, Gas Limit, and Input Data. In particular, From and To represent the sender and recipient, respectively. Value denotes the amount transferred from one smart contract to another. Input Data contains the function’s signature (obtained from the ABI) and its arguments. Finally, the Gas Limit field specifies the amount of cryptocurrency which a miner gets for conveying the transaction. The Ethereum protocol [21] defines the gas cost for each bytecode instruction. For instance, an integer division operation costs 5 units of gas while a store operation on the storage can cost up to 20000. As we will see in Section VII, the gas mechanism plays a key role in several different types of vulnerabilities.

D. Threat Model

To synthesize an adversarial contract, we assume that we can obtain the victim contract’s bytecode and the ABI specifying its public methods. To confirm an adversarial contract is indeed an exploit, we must also be able to invoke public methods by submitting transactions over the Ethereum Blockchain. These requirements are easy to satisfy in practice.

We also visualize this vulnerability pattern in Fig 3. Here, \( arg_0, r_j, \) and \( \text{call} \) represent function arguments, registers, and the CALL instruction (to perform a transaction in Solidity), respectively. We use \([r_j]_i\) to denote the value (either concrete or symbolic) in the register \( r_j \). The \text{interfere?} function, which is defined in section IV, checks the interference between two expressions. The interference \( \text{interfere?} \) (denoted by an arrow in Fig 3) in our system precisely captures the data- and control-dependency. For instance, the vulnerability states that, there exists a CALL instruction for which the beneficiary (i.e., recipient’s address) and value are controlled by the attacker

| From: | 0x7d5c8c3598373757c541bc7d8/dec5fc6bba55ba65 |
| To: | 0x8811fffcc266844e8c3564183897cda7c7/7ab7 |
| Value: | 0.05 Ether |
| Gas Limit: | 31602 |
| Input Data: | 0x087474703a21f26c6f63616c686f73743a135335435 |

TABLE I: A sample transaction [24] obtained from Etherscan

Fig. 3: The key pattern of the BatchOverflow Vulnerability

III. OVERVIEW

In this section, we give an overview of our approach with the aid of a motivating example.

A. Smart Contract Vulnerabilities

A security analyst can specify various types of vulnerabilities that may appear in a smart contract. For instance, a Reentrancy vulnerability [7] occurs when an attacker’s previous invocation is allowed to make new calls to the victim contract before the previous execution is complete. This means that if the call involves money transactions, the attacker can repeatedly trigger many transactions until the current procedure runs out of gas. A Timestamp dependence vulnerability [18], on the other hand, happens when a transaction relies on a certain timestamp, which allows malicious miners to gain advantage by choosing a suitable timestamp.

This section uses the most recent BatchOverflow Vulnerability (CVE-201810299) [20] as a motivating example. Exploits due to this vulnerability have resulted in the creation of trillions of invalid Ethereum Tokens in 2018 [25], causing major exchanges to temporary halt until all tokens could be reassessed. As shown in Fig 4a the batchTransfer function performs a multiplication that can overflow 256 bits, which results in a small value that passes the check at line 12 and further transfers a large amount of tokens to the attacker (line 18).

SMARTSCOPY’s specifications are assertions expressed in the Racket language [26]. In particular, the BatchOverflow Vulnerability can be expressed as follows:

\[
\text{foo}(arg_0, arg_1,...) \{ \\
... \text{\( r_3 = r_1 \otimes r_2 \)} \\
... \text{\( \text{call}(gas, addr, value,...) \)} \\
... \}
\]

We also visualize this vulnerability pattern in Fig 3. Here, \( arg_0, r_j, \) and \( \text{call} \) represent function arguments, registers, and the CALL instruction (to perform a transaction in Solidity), respectively. We use \([r_j]_i\) to denote the value (either concrete or symbolic) in the register \( r_j \). The \text{interfere?} function, which is defined in section IV, checks the interference between two expressions. The interference \( \text{interfere?} \) (denoted by an arrow in Fig 3) in our system precisely captures the data- and control-dependency. For instance, the vulnerability states that, there exists a CALL instruction for which the beneficiary (i.e., recipient’s address) and value are controlled by the attacker.
contract PausableToken {
    bool flag = false;
    function makeFlag(bool fg) {
        flag = fg;
    }
    function batchTransfer(address[] _receivers, uint256 _value) {
        uint cnt = _receivers.length;
        uint256 amount = uint256(cnt) * _value;
        require(flag);
        require((balances[msg.sender] >= amount));
        balances[msg.sender] = balances[msg.sender].sub(amount);
        for (uint i = 0; i < cnt; i++) {
            address recv = _receivers[i];
            balances[recv] = balances[recv].add(_value);
            Transfer(msg.sender, recv, _value);
        }
        return true;
    }
}

contract Attacker {
    function exploit() {
        VulContract v;
        v.makeFlag(true);
        v.batchTransfer([0x123, 0x456], 2**256 - 1);
    }
}

(a) The Vulnerable Program

(b) An Attack Program

(c) Contract Application Binary Interface (ABI) for the vulnerable contract in Fig 4b

Fig. 4: A running example to show the BatchOverflow Vulnerability

(line 5, 6). Furthermore, the transaction’s value is influenced by a register (line 4) used in an arithmetic operation that overflows (line 2, 3).

Once a security analyst expresses the Batchoverflow vulnerability, the next step is to construct an attack to confirm that the vulnerability indeed exists in the victim contract. Doing so manually is challenging, however, because the analyst has to understand the semantics of the smart contract and simulate all possible interactions that an attacker may perform. As a result, the analysis process is both tedious and error-prone.

B. SMARTScopy

SMARTScopy helps automate this process by searching for attacks that exploit a given vulnerability in a victim contract. As shown in Fig 2, the tool takes as input a potential vulnerability \( V \) expressed as declarative specifications. If \( V \) exists in the victim contract, SMARTScopy automatically synthesize an attack program that exploits \( V \). In practice, an attacker typically interacts with a vulnerable contract through its public methods defined in the ABI. Therefore, our goal is to construct an attack program that exploits the victim’s ABI and that contains at least one concrete trace where \( V \) holds.

To achieve this goal, SMARTScopy models the executions of a smart contract as state transitions over registers, memory, and storage. The vulnerability \( V \) is expressed in Racket as a boolean predicate over these state transitions. The technical challenge addressed by SMARTScopy is to efficiently search for an attack program where \( V \) holds.

To illustrate the difficulty of this task, consider the problem of synthesizing an attack program that exploits the BatchOverflow vulnerability in Fig 4. The attack program performs a complex three-step interaction with the victim contract. First, the attacker must set the storage variable \( flag \) to true to pass the check at line 11. Next, it needs to assign a large number to \( _value \) that leads to an overflow at line 10. Finally, it specifies the attacker’s address as the beneficiary of the transaction (line 18). Synthesizing this attack program involves discovering which methods to call, in what order, and with what arguments.

To find the desired attack program, it is not feasible to brute-force generate all possible concrete programs and explore the space of their concrete traces. As we elaborate in Section III-A, the search space is exponential to the size of the attack program as well as its the number of branches.

To address this challenge, Section V proposes a novel summary-based symbolic evaluation technique that significantly reduces the number of instructions in the victim contract that SMARTScopy has to execute symbolically (Section V). Intuitively, our summary-based symbolic evaluation enables SMARTScopy to only preserve state transitions that are persistent across different transactions and are sufficient to answer the vulnerability query.

Even with our summary-based symbolic evaluation, the search space of attack candidates is still too large for brute-force search. To further improve the performance, Section VI introduces three optimizations. First, instead of exploring the space of concrete programs, we leverage ROSETTE [17] to explore the symbolic programs (Section VI-A). Second, instead of eagerly explore the space of symbolic programs, we design a simple but effective early pruning strategy that allows SMARTScopy to prune infeasible symbolic candidates before executing them (Section VI-C). Finally, instead of executing each symbolic program sequentially, we partition the search space by case splitting on the range of symbolic variables, which enables SMARTScopy to simultaneously explore multiple symbolic candidates (Section VI-B).
(\text{var}) ::= \text{def-sym} \ (\text{id} \ \tau) \\
\quad (\tau \in \{\text{boolean, number}\})

(\text{pc}) ::= (\text{const}) \mid (\text{var})

(\text{expr}) ::= (\text{const}) \mid (\text{var}) \mid (\text{expr}) \oplus (\text{expr}) \\
\quad (\oplus \in \{+, -, \times, /, \vee, \land, \ldots\})

(\text{stmt}) ::= (\text{var}) := (\text{expr}) \\
| (\text{var}) := \text{mload} \ (\text{var}) \mid \text{mstore} \ (\text{var}) \ (\text{var}) \\
| (\text{var}) := \text{sload} \ (\text{var}) \mid \text{sstore} \ (\text{var}) \ (\text{var}) \\
| (\text{var}) := \{\text{balance, gas, address}\}

(\text{stmts}) ::= (\text{stmt}) \mid (\text{stmts}) \mid \text{sha3} \ (\text{var}) \ (\text{var}) \\
| \text{jump} \ (\text{pc}) \ (\text{expr}) \mid \text{jump} \ (\text{pc}) \ \text{no-op} \\
| \text{call} \ (\text{var}) \ (\text{var}) \ (\text{var}) \mid \text{selfdestruct} \ (\text{var})

(\text{param}) ::= (\var)

(\text{params}) ::= (\param) \mid (\param), (\params)

(\text{prog}) ::= \lambda(\text{params}). \ (\text{stmts})

Fig. 5: Intermediate Language for Smart Contract

IV. PROBLEM FORMULATION

This section formalizes the semantics of smart contracts, shows how to express Smart Contract Vulnerabilities, and defines what it means for a vulnerability to appear in a smart contract.

A. Smart Contract Language

Figure 5 shows the core features of our intermediate language for smart contracts. This language is a superset of the EVM language. It includes standard EVM bytecode instructions such as assignment (\(x := e\)), memory operations (\text{mstore, mload}), storage operations (\text{sstore, sload}), hash operation (\text{sha3}), sequential composition (\(s_1; s_2\)), conditional (\text{jumpi}) and unconditional jump (\text{jump}). It also includes the EVM instructions specific to smart contracts: \text{call} transfers the balance from the current contract to a recipient whose address is specified as the argument, \text{balance} accesses the current account balance, and \text{selfdestruct} terminates a contract and transfers its balance to a given address. Finally, our language extends EVM with features that facilitate symbolic evaluation, including \textit{symbolic variables} (introduced by \text{def-sym}) and \textit{symbolic expressions} (obtained by operating on symbolic variables) whose concrete values will be determined by an off-the-shelf SMT solver \cite{28}.

We define the semantics of the language operationally, as shown in Figure 5. The meaning of each statement is given by a \textit{state transition} rule that specifies the statement’s effect on the program state. We define states and transitions as follows.

\textbf{Definition 1. (Program State)} The Program State \(\Gamma\) consists of a stack \(E\), memory \(M\), persistent storage \(S\), global properties (e.g., balance, address, timestamp) of a smart contract, and the program counter \(pc\). We use \(e_i\), \(m_i\), and \(\mu_i\) to denote variables from the stack, memory, and storage, respectively.

A program state also includes a model of the gas system in EVM, but we omit this part of the semantics to simplify

\begin{align*}
\text{no-op} & : s = \text{no-op} \\
\Gamma \vdash s : \Gamma'[pc++]
\end{align*}

\begin{align*}
\text{jump} & : e : v \\
\Gamma \vdash e : \Gamma = \Gamma[x \leftarrow v, pc \leftarrow i] \\
\Gamma \vdash s : \Gamma'
\end{align*}

\begin{align*}
\text{sym} & : s = (\text{param} := \text{def-sym}(e, \tau)) \\
\Gamma \vdash s : \Gamma'[\text{param} \leftarrow v'] \\
\Gamma \vdash s \ : \ \Gamma'[pc++], v
\end{align*}

\begin{align*}
\text{assign} & : s = (x := e) \\
\Gamma \vdash e : \Gamma = \Gamma'[x \leftarrow v] \\
\Gamma \vdash s \ : \ \Gamma'[pc++]
\end{align*}

\begin{align*}
\text{biop} & : s = (x := e_1 \oplus e_2)(\oplus \in \{+, -, \times, /\}) \\
\Gamma \vdash e_1 : \Gamma = \Gamma'[x \leftarrow v] \\
\Gamma \vdash e_2 : \Gamma = \Gamma'[x \leftarrow v] \\
\Gamma \vdash s \ : \ \Gamma'[pc++]
\end{align*}

\begin{align*}
\text{seq} & : s = s_1 : s_2 \\
\Gamma \vdash s_1 : \Gamma_1, v_1 \\
\Gamma \vdash s_2 : \Gamma_2, v_2 \\
\Gamma \vdash s : \Gamma_2, v_2
\end{align*}

\begin{align*}
\text{jumpi} & : e : v \\
\Gamma \vdash e : \Gamma = \Gamma[x \leftarrow v, pc \leftarrow i] \\
\Gamma \vdash s : \Gamma'
\end{align*}

\begin{align*}
\text{call} & : e_1 : e_2 : e_3 \\
\Gamma \vdash e_1 : \Gamma = \Gamma'[x \leftarrow v] \\
\Gamma \vdash e_2 : \Gamma = \Gamma'[x \leftarrow v] \\
\Gamma \vdash e_3 : \Gamma = \Gamma'[x \leftarrow v] \\
\Gamma \vdash s \ : \ \Gamma'[pc++], r_1
\end{align*}

\begin{align*}
\text{sha} & : s = (\text{sha3} \ m \ e) \\
\Gamma \vdash e : \Gamma = \Gamma'[x \leftarrow v] \\
\Gamma \vdash m : \Gamma = \Gamma'[x \leftarrow v] \\
\Gamma \vdash s : \Gamma'[pc++], v
\end{align*}
the presentation. If a state maps a variable to a symbolic expression, we call it an abstract state.

**Definition 2. (State Transition over statement s)** A State Transition $\Gamma^\prime$ over a statement $s$ is denoted by a judgment of the form $\Gamma \vdash s : \Gamma^\prime, v$. The meaning of this judgment is the following: assuming we successfully execute $s$ under program state $\Gamma$, it will result in value $v$ and the new state is $\Gamma^\prime$. We use $\Gamma \vdash s : \bot$ to indicate failure.

Most of the rules in Figure 6 specify the standard semantics of EVM instructions. For example, the biop rule describes the meaning of binary operations: it first looks up the values (concrete or symbolic) of the operands in the current program state $\Gamma$, applies the binary operator to those values (i.e., $v_1, v_2$), and then binds the result to the target variable, increases the program counter, and produces a new program state $\Gamma^\prime$. The sstore, sload, jmp, and seq rules are also standard.

The sym, sha3, and call rules, on the other hand, are tailored for (efficient) symbolic evaluation. The sym rule introduces symbolic values into the program state. The construct $\langle e, \tau \rangle$ denotes a fresh symbolic variable $e$ of type $\tau$, which is bound to the def-sym parameter in the new program state $\Gamma^\prime$. Here, we do not increase the program counter as the symbolic binding is not an EVM instruction. The sha3 and call instructions are part of EVM, but we overapproximate their semantics with uninterpreted functions to produce more tractable vulnerability queries.

The standard semantics of the sha3 instruction is to obtain a memory location by hashing a memory address and offset. However, applying hashing functions to symbolic arguments results in hard-to-solve queries. The sha3 rule therefore uses an uninterpreted function, denoted by sha3, to model the original hash function.

As mentioned earlier, the call instruction is used to initiate a transaction with another contract, whose address is specified as an argument. The call rule uses an uninterpreted function, denoted by call, to model the effect of the call instruction. Note that the rule also records the return value of each call using a special variable $r_1$ in $\Gamma$, where $l$ is the location of the call command. This handling of call instructions is key to our summary-based symbolic evaluation, as explained in Section V.

**Example 1.** Figure 7a shows a smart contract written in Solidity. To analyze this contract, our system first translates it to the program in Figure 7b, using the intermediate language in Figure 5. The resulting program is then evaluated symbolically using the operational semantics in Figure 6. For instance, after executing the statement at line 2 in Figure 7b, register r1 holds a symbolic value represented by $\langle \text{amount} - 1 \rangle$. On the other hand, since SMARTSCOPY does not model the event system in Solidity, we simply turn all its corresponding instructions (e.g., line 14 in Figure 7a) into no-op.

**B. Smart Contract Vulnerabilities**

Having defined the meaning of smart contracts, we now describe how to formally express smart contract vulnerabilities and what it means for a vulnerability to appear in a program.

**Definition 3. (Vulnerability)** A Vulnerability $V$ is a predicate over a set of variables $V$ in the program state. A vulnerability $V$ appears in the program $P$ if the execution of $P$ can reach a program state $\Gamma^\prime$ that satisfies $V$:

$$\Gamma^\prime \models V$$

The rest of this section introduces a few representative vulnerabilities, and shows how they are encoded as formulas in SMARTSCOPY. But first, we introduce an auxiliary function interfere? which will be used by several vulnerabilities.

**Definition 4. (Interference)** A symbolic variable $e$ interferes with a symbolic expression $e'$ if they satisfy the following constraint:

$$\exists v_0, v_1, e[\langle v_0/v \rangle] \neq e'[\langle v_1/v \rangle] \land (v_0 \neq v_1)$$

Intuitively, changing $v$‘s value will also affect $e$‘s output, which is denoted as “(interfere? $v$ $e$)”. Interference precisely captures the data- and control-dependencies between two expressions and turns out to be the necessary condition of many exploits.

Section III describes the BatchOverflow vulnerability, which enables an attacker to perform a multiplication that overflows and transfers a large amount of tokens on the attacker’s behalf. This vulnerability can be formalized as follows:

**Vulnerability 1. BatchOverflow**

$$\exists \text{arg0, arg1, r1, r2, r3, call} \quad r_3 = (r_1 \otimes r_2) \land [r_2] > [r_3] \land (\text{interfere? } r_2 \text{ call.value}) \land (\text{interfere? } \text{arg0 call.addr}) \land (\text{interfere? } \text{arg1 call.value})$$

In other words, the victim program contains a call instruction whose beneficiary and value can be controlled by the attacker. Furthermore, the transaction value is also influenced by a variable from an arithmetic operation that overflows.

A Timestamp Dependency vulnerability occurs if a transaction depends on a timestamp:

**Vulnerability 2. Timestamp Dependency**

$$\exists \text{timestamp, call.call.value} > 0 \land (\text{interfere? timestamp call.value})$$

This vulnerability enables a malicious miner to gain an advantage by choosing a suitable timestamp for a block.

For some critical instructions such as delegatecall and call, runtime errors will not lead to a rollback of the current state and the programmer is responsible for manually checking the return values and restoring the program state. Failing to do so can lead to an Unchecked-send Vulnerability with unexpected behavior [29]. We formalize the absence of this check as follows:

**Vulnerability 3. Unchecked-send (Gasless-send)**

$$\forall \text{call.ret}, \exists \text{jmp.var}(\text{interfere? call.ret jmp.var})$$
Vulnerability 4. Reentrancy

\[ l[i] = \text{"call"} \land l[j] = \text{"call"} \land l[k] = \text{"store"} \land l[i].\text{gas} > 2300 \land \text{interfere? arg } l[i].\text{addr} \] (4)

where \( l \) is an execution trace.

In other words, if an attack program has the minimum gas (i.e., 2300) to control the recipient of a transaction and generate consecutive call instructions before updating the storage, there may exist a Reentrancy vulnerability.

C. Attack Synthesis.

Given a vulnerability query, we are interested in synthesizing an attack program that can exploit this vulnerability in a victim contract. The basic building blocks of an attack program are called components, and each component \( C \) corresponds to a public function provided by a victim contract. We use \( \Upsilon \) to denote the union of all publicly available methods.

Definition 5. (Component) A Component \( C \) from an ABI configuration is a pair \((f, \tau)\) where:

- \( f \) is \( C \)'s name.
- \( \tau \) is the type signature of \( C \).

Example 2. Considering the ABI configuration in Figure 4c, its first element (line 2-12) declares a component for the problematic batchTransfer method in figure 4a. In particular, this component takes inputs as an array of address and a 256-bit integer (uint256).

We represent a set of candidate attack programs as a symbolic program, which is a sequence of holes to be filled with components from \( \Upsilon \). The synthesizer fills these holes to obtain a concrete program that exploits a given vulnerability.

Definition 6. (Symbolic Attack Program) Given a set of components \( \Upsilon = \{(f_1, \tau_1), \ldots, (f_N, \tau_N)\} \), a symbolic attack program \( S \) for \( \Upsilon \) is a sequence of statement holes of the form

\[ \text{choose}(f_1(\overline{v}_{\tau_1}), \ldots, f_N(\overline{v}_{\tau_N})); \]

where \( f_i(\overline{v}_{\tau_i}) \) stands for the application of the \( i \)-th component to fresh symbolic values of types specified by \( \tau_i \).

Definition 7. (Concrete Attack Program) A concrete attack program for a symbolic program \( S \) replaces each hole in \( S \) with one of the specified function calls, and each symbolic argument to a function call is replaced with a concrete value.

Example 3. Here is a symbolic program that captures the attack candidate in Fig 4d:

\[ \text{choose(makeFlag}(r_1)); \text{batchTransfer}(y_1,z_1)); \text{choose(makeFlag}(r_2)); \text{batchTransfer}(y_2,z_2)); \]

And here is a concrete attack program for this symbolic attack:

\[ \text{makeFlag}(true); \text{batchTransfer}([0x123,0x345], 2^{256} - 1); \]
Note that we use the `choose` construct to represent holes in symbolic programs only for notational convenience. Since our smart contract language supports symbolic values, every instance of `choose` can be expressed using a conditional statement that guards the specified choices with fresh symbolic booleans. For example, `choose(e_1, e_2)` is a notational shorthand for the statement `if b_1 then e_1 else e_2`, where `b_1` is a fresh symbolic boolean value. A concrete attack program therefore substitutes concrete values for the implicit `choose` guards and the explicit function arguments of a symbolic attack program. So, all attack programs are expressible in our smart contract language with no extra machinery.

Since attack programs are valid programs in our language, their semantics is given by the rules in Figure 6. We write \([S_0; \ldots; S_n;]\) to represent the result of executing the attack program \(S = S_0; \ldots; S_n;\) from the program state \(\Gamma\). If \(S\) is a symbolic attack program, then \([S_0; \ldots; S_n;]\) represents the states \(\Gamma^*\) reachable by all concrete programs for \(S\) starting from the state \(\Gamma\). The goal of attack synthesis is to find a concrete program \(P\) for a given symbolic program \(S\) such that \(P\) reaches a state satisfying a desired vulnerability query.

**Definition 8.** (Problem Specification) The specification for our attack synthesis problem is a tuple \((\Gamma_0, \mathcal{V}, S)\) where:

- \(S\) is a symbolic attack program for the set of components \(\mathcal{V}\) of a victim contract \(\mathcal{V}\).
- \(\Gamma_0\) is the initial state of the symbolic attack program, obtained by executing the victim’s initialization code.
- \(\mathcal{V}\) is a first-order formula over program states \(\Gamma^*\) reachable from \(\Gamma_0\) by the attack program \(S\).

**Definition 9.** (Attack Synthesis) Given a specification \((\Gamma_0, \mathcal{V}, S)\), the Attack Synthesis problem is to find a concrete attack program \(P\) for \(S\) such that:

- \(\llbracket P \rrbracket_{\Gamma_0} = \Gamma\)
- \(\Gamma \models \mathcal{V}\)

In other words, executing the concrete attack program \(P\) from the initial state \(\Gamma_0\) results in a program state \(\Gamma\) that satisfies \(\mathcal{V}\).

V. SUMMARY-BASED SYMBOLIC EVALUATION

Solving the attack synthesis problem involves searching for a concrete program \(P\) in the space of candidate attacks defined by a symbolic program \(S\). SMARTSCOPY delegates this search to an off-the-shelf SMT solver, by using symbolic evaluation to reduce the attack synthesis problem to a satisfiability query. Given a specification \((\Gamma_0, \mathcal{V}, S)\), SMARTSCOPY evaluates \(S\) on the state \(\Gamma_0\) to obtain the state \([S]_{\Gamma_0}\), and then uses the solver to check the satisfiability of the formula \(\exists \vec{v}. \mathcal{V}(\vec{v}, [S]_{\Gamma_0})\), where \(\vec{v}\) denotes the symbolic variables in \(S\). A model of this formula, if it exists, binds every variable in \(\vec{v}\) to a concrete value, and so represents a concrete attack program \(P\) for \(S\) that triggers the vulnerability \(\mathcal{V}\).

But computing \([S]_{\Gamma_0}\) is expensive, as it relies on symbolic execution \([17]\). In particular, evaluating \(S\) involves evaluating each of its `choose` statements, which, in turn, requires symbolically executing each function call in that statement. So, for a symbolic program of length \(K\), every public function in the victim contract must be symbolically executed \(K\) times on different symbolic arguments. As we will see in section VII this direct approach to evaluating \(S\) does not scale to real contracts that contain a large number of complex public functions. To mitigate this issue, we use a summary-based symbolic evaluation that performs symbolic execution of each public method only once.

Our approach is based on the following insight. An attack program performs a sequence of transactions—i.e., method invocations—that manipulate the victim’s persistent storage and global properties. The transactions that comprise an attack exchange data and influence each other’s control flow exclusively through these two parts of the program state. So, if we can faithfully summarize the effects of a public method on the persistent storage and global properties, evaluating this summary on the symbolic arguments passed to the method is equivalent to symbolically executing the method itself.

**Definition 10.** A summary \(M\) in our system is a pair \(s@\phi\) where \(s\) represents a statement that has a side effect on the persistent state (i.e., storage and global properties) of a smart contract, and \(\phi\) denotes the path condition of executing \(s\).

We generate such faithful method summaries in two steps. First, we use the rules in Figure 5 to execute the method on a program state \(\Gamma_A\) that maps every state variable (i.e., persistent storage location, global property, etc.) to a fresh symbolic variable of the right type. This symbolic execution step produces a path condition and symbolic inputs for each instruction that capture every possible way to reach and execute the instruction within the given method. Next, we use the procedure in Figure 6a to generate the method summary\(^1\). Given a storage-store instruction `sstore(x,y)` and its path condition, we generate a “summary sstore” statement (i.e., `sstore`) that takes as input the name of the storage variable (i.e., \(x\)) and the symbolic expression \([y]\) held in the register \(y\). Similarly, given a `call(gas,addr,value)` instruction and path condition, we emit its “summary call” statement (i.e., `call`) that takes as input the symbolic expressions of the instruction’s gas consumption, recipient address, and amount of cryptocurrency, respectively. All other instructions are omitted from the summary since they have no effect on the persistent state. By construction, our summary therefore precisely captures all of the method’s effects on the persistent state.

**Example 4.** Figure 7 shows the summary of the program in Figure 4. Using the rule in Figure 9 our tool summarizes the side effects of the `call` and `sstore` instructions at lines 3 and 4, respectively. The remaining instructions (lines 6–9) are omitted from the summary.

Given a method summary and a program state \(\Gamma\), we use the procedure in Figure 8 to reproduce the effects of executing the method symbolically on \(\Gamma\) as follows. Recall that we

\(^1\) We omitted the details of other instructions such as `selfdestruct` and `delegatecall`.
(define (get-summary s \phi)
  (match s
    [call(x, y, z) \\call([x], [y], [z]) \\phi]
    [sstore(x, y) \\sstore(x, [y]) \\phi]
    [\_ \_ no-op]])

(a) Procedure for Summary Generation

(define (interpret-summary \phi \Gamma)
  (match \phi
    [call(xr, yr, zr) \\when\phi (call(xr, yr, zr))]
    [sstore(xr, yr) \\when\phi (sstore(xr, yr))]
    [\_ \_ no-op]])

(b) Procedure for Summary Interpretation

Fig. 8: Summary Generation & Interpretation

This section discusses the design and implementation of SMARTSCOPY, as well as two key optimizations that enable our tool to efficiently solve the synthesis attack problem.

A. Symbolic Computation Using Rosette

SMARTSCOPY leverages Rosette \cite{17} to symbolically search for attack programs. Rosette is a programming language that provides facilities for symbolic evaluation. These facilities are based on three constructs: assertions, symbolic values, and (satisfiability) queries. Rosette programs use assertions and symbolic values to formulate queries about program behavior, which are then solved with off-the-shelf SMT solvers. For example, the (solve expr) query searches for a binding of symbolic variables to concrete values that satisfies the assertions encountered during the symbolic evaluation of the program expression expr. SMARTSCOPY uses the solve query to search for a concrete attack program.

Figure 9 shows the implementation of SMARTSCOPY in Rosette. The tool takes as input a vulnerability specification \mathcal{V}, the components \mathcal{T} of a victim program, and a bound \mathcal{K} on the length of the attack program. Given these inputs, lines 2–4 use \mathcal{T} to construct a symbolic attack program of length \mathcal{K}. Next, lines 5–13 run the victim’s initialization code to obtain the initial program state, i-pstate, for the attack. Then, line 14 evaluates the symbolic attack program on the initial state to obtain a symbolic output state, o-pstate. Finally, lines 15–16 use the solve query to search for a concrete attack program that satisfies the vulnerability assertion.

The core of our tool is the interpreter for our smart contract language (Figure 5), which implements the operational semantics given in Figure 6. We use this interpreter to compute the symbolic summaries of the victim’s public methods (Section V) and to evaluate symbolic attack programs. The interpreter itself does not implement symbolic execution; instead, it uses Rosette’s symbolic evaluation engine to execute programs in our language on symbolic values.

Another key component of SMARTSCOPY is the translator that converts EVM bytecode into our language (Figure 5). The translator leverages the Vandal Decompiler \cite{14} to soundly convert the stack-based EVM bytecode into its corresponding three-address format in our language. The jump targets are resolved through abstract interpretation \cite{30}. We use the translator to convert victim contracts to the SMARTSCOPY language for attack synthesis. Both the translator and the interpreter support all the instructions defined in the Ethereum specification \cite{21}.

B. Parallel Synthesis using Hoisting

SMARTSCOPY uses summary-based symbolic evaluation to efficiently reduce attack synthesis problems to satisfiability queries. But the resulting queries can still be too difficult (for...
both Rosette and the underlying solver) to solve in practice, especially when the victim contract has many public methods. So to further improve performance, SMARTCOPY exploits the structure of symbolic attack programs (Definition 6) to decompose the single solve query in Figure 9 into multiple smaller queries that can be solved quickly and in parallel, without missing any concrete attacks.

The basic idea is as follows. Given a set of $N$ components and a bound $K$ on the length of the attack, lines 2–4 create a symbolic attack program of the following form:

\[
\text{choose}_1(f_1(v_1^{τ_1}), ..., f_N(v_N^{τ_N}));
\]

\[
\vdots
\]

\[
\text{choose}_K(f_1(v_1^{τ_N}), ..., f_N(v_K^{τ_N}));
\]

This symbolic attack encodes a set of concrete attacks that can also be expressed using $N^K$ symbolic programs that fix the choice of the method to call at each line, but leave the arguments symbolic. So, we can enumerate these $N^K$ programs and solve the vulnerability query for each of them, instead of solving the single query at line 15. This approach essentially hoists the symbolic boolean guards out of the choose statements in the original query, and SMARTCOPY explores all possible values for these guards explicitly, rather than via SMT solving. As we show in Section VII hoisting the guards leads to significantly faster synthesis, both because it enables parallel solving of the smaller queries, and because the smaller queries can be solved quickly.

C. SMT-based Early Pruning

In addition to hoisting, we also design a simple but effective early pruning strategy that allows SMARTCOPY to prune infeasible symbolic programs before executing them. The intuition behind our early pruning strategy is that all attacks expressible in SMARTCOPY (e.g., [7], [8], [9]) invoke at least one public method that manipulates persistent storage and at least one public method that transfers cryptocurrency using the call instruction. In other words, a successful attack executes at least one store instruction followed by at least one call instruction. We express our early pruning strategy using the following Rosette program:

1 (define (may-store-and-call? p)
2   (solve (exists (list i j)
3           (and (< i j) (= (type p[i]) 'store))
4           (= (type p[j]) 'call))))

This procedure queries the solver to find out if the given symbolic program $p$ contains any concrete attack program that executes a call after a store. This query is much faster to solve than a vulnerability query, so if $p$ contains no feasible candidate, SMARTCOPY does not run the vulnerability query for it.

VII. Evaluation

We evaluated SMARTCOPY by conducting two experiments that are designed to answer the following questions:

- **Q1: Expressiveness**: Can SMARTCOPY express the specifications of real world vulnerabilities?
- **Q2: Effectiveness**: How does SMARTCOPY compare against state-of-the-art analyzers for smart contracts?
- **Q3: Efficiency**: How much does summary-based symbolic evaluation improve the performance of SMARTCOPY?

To answer these questions, we perform a systematic evaluation by running SMARTCOPY on the entire set of smart contracts from Etherscan. Using a snapshot from August 30, 2018, we obtained a total number of 25,983 smart contracts. Similar to the teEther paper, we restrict the maximum size of our attack programs to three. All experiments in this section are conducted on a t3.2xlarge machine on Amazon EC2 with an Intel Xeon Platinum 8000 CPU and 32G of memory, running the Ubuntu 18.04 operating system and using a timeout of 10 minutes for each smart contract.

A. Expressiveness of SMARTCOPY

To understand the expressiveness of our tool, we encoded the common vulnerabilities in smart contracts described in prior work [18], [31] and on social media [25]. In particular, Table 1 summarizes the expressiveness of existing tools for Smart Contract security, ordered by publish date. Note that our tool supports not only well-known vulnerabilities such as Reentrancy, Timestamp Dependency, and Arithmetic operations (i.e., over/underflow), but also recent attacks such as the short address attack and the BatchOverflow vulnerability discussed in Section III. Prior tools express a portion of these vulnerabilities. For instance, the popular Oyente tool, which is also based on symbolic execution, does not support vulnerabilities such as unchecked calls, short address, and out-of-gas-DoS. Static analysis tools such as Secureiti [12] and MadMax [14] do not support complex arithmetic vulnerabilities. Most importantly, unlike SMARTCOPY, none of them can generate exploits for vulnerabilities. The teEther and the ContractFuzzer tools can automatically generate exploits, but their systems only support a small class of vulnerabilities.

There are some vulnerabilities that our tool does not support well. For instance, a Transaction-Ordering Dependency (TOD) is a race condition vulnerability, and exploiting it requires synthesizing a pair of programs that exhibit the race. In the future, we plan to explore relational synthesis to handle attacks that require multiple programs. Another source of limitation is denial-of-service (DoS) attacks that involve loops, which our tool unrolls during symbolic execution, and the unrolling bound may not be big enough to trigger the vulnerability.

B. Comparison with Existing Tools

To demonstrate the advantages of our proposed approach, we compare SMARTCOPY against two state-of-the-art analyzers that are publicly available: Oyente, based on symbolic execution, and ContractFuzzer, based on dynamic random testing.

1) **Comparison with Oyente**: We first compare with Oyente [11], which takes as input a smart contract and

2Other tools like teEther and Secureiti are not available for comparison at the time of this submission.
checks whether there are concrete traces that match the tool’s predefined security properties. If so, the tool returns a counterexample as the exploit. We evaluate OYENTE and SMARTSCOPY on the Etherscan data set, and both systems use a timeout of ten minutes.

The OYENTE tool supports four different types of vulnerabilities, namely, call-stack-limit, Timestamp dependency [10], Reentrancy [7], and Transaction-Ordering dependency (TOD) [10]. Since the call-stack-limit vulnerability had already been fixed by the Solidity team and the TOD vulnerability requires synthesizing multiple programs, we will cover the remaining two vulnerabilities.

b) Summary of results: The results of our evaluation are summarized in Table III. In particular, for the Timestamp dependency vulnerability, there are 485 benchmarks where both tools report a vulnerability and find the exploit. 39 benchmarks are flagged as vulnerable by OYENTE but SMARTSCOPY cannot find the exploit. We manually inspected the source code of those benchmarks and confirm that 30 of them are false positives. On the other hand, 842 benchmarks are flagged as safe by OYENTE while SMARTSCOPY manages to find their exploits. To verify the reports of our tool, we randomly select 20 benchmarks and confirm 18 of them are actually vulnerable. In the meantime, we also contacted the author of OYENTE and confirmed our report.

For the Reentrancy vulnerability, 49 benchmarks are flagged by both tools. 41 benchmarks are flagged as vulnerable by OYENTE while SMARTSCOPY cannot find the exploits. After manual inspection, we confirm all of them are false positives. In contrast, 128 benchmarks are marked as safe but SMARTSCOPY successfully finds their exploits, and we manage to reproduce 102 of the attacks in our testbed.

To further understand the effectiveness of both tools, we randomly pick 20 samples from a subset of the data where each contract is flagged as vulnerable by at least one tool. We repeat this process three times and report the average. As shown in Table IV for the Timestamp vulnerability, the FN and FP rates of SMARTSCOPY are 7% and 10%, while the FN and FP rates of OYENTE on our selected data set are 36% and 35%. The result on the Reentrancy vulnerability is similar: the FN and FP rates of SMARTSCOPY are 14% and 5%, while the FN and FP rates of OYENTE are 43% and 37%.

c) Performance: OYENTE takes an average of 91 seconds to analyze a contract, while SMARTSCOPY only takes an average of 8 seconds for this data set.

d) Discussion: To understand why OYENTE has higher false positive and negative rates than SMARTSCOPY, we manually inspected 20 randomly chosen samples from each category. The results of this analysis are as follows.

The high false negative rate in OYENTE is caused by low coverage on the corresponding benchmarks. Specifically, in the presence of large and complex benchmarks, OYENTE fails to generate traces that trigger the vulnerability. Moreover, since the Keccak-256 hash function is ubiquitous in smart contracts, and hard for the solver to reason about, OYENTE fails to cover the code regions that have dependencies on the hash function.

The false positives in OYENTE can be attributed to two root causes. The first is that the tool does not model the semantics of the gas system, and its query language cannot reason about gas consumption in a smart contract. For instance, OYENTE will report spurious Reentrancy vulnerabilities even though the gas specified by the victim is insufficient for an attacker to generate the exploit. On the other hand, since SMARTSCOPY precisely models the semantics of the gas system, we are able to achieve a low false positive rate. The second cause of false positives is due to the exploration of paths that an attacker cannot trigger. For instance, OYENTE marks the following code as Reentrancy vulnerability even though an attacker has no permission to trigger it.

```solidity
public function mintETHRewards(
    address _contract, uint256 _amount
) onlyManager() {
    require(_contract.call.value(_amount)());
}
```
We also investigated the cause of false positives reported by SMARTSCOPY. It turns out that the false positives are caused by the imprecision of our queries. Recall from Section IV-B that we use a specific pattern of traces to overapproximate the behavior of the Reentrancy attack. While effective and efficient in practice, our query may generate spurious exploits that are infeasible. To mitigate this limitation, one compelling approach for developing secure smart contracts is to ask the developers to provide invariants for preventing the vulnerabilities, and then use SMARTSCOPY to search for exploits that violate the invariants.

C. Comparison with CONTRACTFUZZER

We further compared SMARTSCOPY against CONTRACTFUZZER [13], a recent smart contract analyzer based on dynamic fuzzing. Specifically, CONTRACTFUZZER takes input as the ABI interfaces of smart contracts and randomly generates inputs invoking the public methods provided by the ABI. To verify the correctness of the exploits, CONTRACTFUZZER implements oracles for different vulnerabilities by instrumenting the Ethereum Virtual Machine (EVM) with extra assertions.

We use the docker image [33] provided by the author of CONTRACTFUZZER. The original paper does not discuss the performance of the tool, but from our experience, CONTRACTFUZZER is slow, taking more than 10 mins to fuzz a smart contract. Since it would be time-consuming to run CONTRACTFUZZER on the Etherscan data set, we evaluate both tools on the 33 benchmarks from the CONTRACTFUZZER artifact [34] plus another 67 random samples from Etherscan for which we know the ground truth.

a) Summary of results: The results of our evaluation are summarized in Table V. In particular, for the timestamp dependency, CONTRACTFUZZER flags 13 benchmarks as vulnerable. However, 4 of them are false alarms, and it fails to detect 7 vulnerable benchmarks. On the other hand, SMARTSCOPY detects most of the benchmarks with only one false negative, which is caused by a timeout on the Vandal decompiler [14].

Similarly, for the Gasless-send vulnerability, 14 benchmarks are flagged by CONTRACTFUZZER. However, 3 of them are false positives, and 6 vulnerable benchmarks can not be detected within 10 minutes. In contrast, SMARTSCOPY successfully generates exploits for all the vulnerable benchmarks.

b) Performance: On average, it takes CONTRACTFUZZER 10 mins to analyze a smart contract. SMARTSCOPY takes an average of 11 seconds on this data set.

c) Discussion: The cause of false negatives in CONTRACTFUZZER is easy to understand as it is based on random, rather than exhaustive, exploration of an extremely large search space. So if there are relatively few inputs in this space that lead to an attack, CONTRACTFUZZER is unlikely to find it within the given time bound (10 minutes). On the other hand, the false positives in CONTRACTFUZZER are caused by the limited expressiveness of its assertion language. For instance, the Time Dependency is defined as the following assertion in CONTRACTFUZZER:

\[
\text{TimestampOp} \land (\text{SendCall} \lor \text{EtherTransfer})
\]

The assertion raises a Time Dependency vulnerability if the smart contract contains the timestamp and call instructions. It is easy to raise false alarms with this assertion if the call instruction does not depend on timestamp. On the other hand, the interfere? function enables SMARTSCOPY to reason about this dependency precisely.

D. Impact of Summary-based Symbolic Evaluation

To understand the impact of our summary-based symbolic evaluation described in Section V, we run SMARTSCOPY on the Etherscan data set with \((S^\dagger)\) and without \((S^0)\) computing the summary. To speed up the evaluation, for both settings, we enable the early pruning and parallel synthesis optimizations discussed in Section VI.

As shown in Table VI if we exclude the benchmarks that timeout in 10 mins, the mean time of our summary-based symbolic evaluation is only 8 seconds, while it takes 35 seconds without computing the summary. Furthermore, 1846 benchmarks time out for both settings, and only 548 benchmarks time out on \(S^\dagger\) but not on \(S^0\). However, without computing the summary, 17454 (i.e., 69.8\%) benchmarks time out. The result confirms that the summary-based technique is key to the efficiency of SMARTSCOPY.

E. A case study on the recent BatchOverflow vulnerability

To evaluate whether SMARTSCOPY can discover new vulnerabilities in real world smart contracts, we conduct a case study on the recent BatchOverflow Vulnerability. As we mentioned in Section III exploits due to this vulnerability have resulted in the creation of trillions of invalid Ethereum Tokens in 2018 [25], causing major exchanges to temporary halt until all tokens could be reassessed. We note that generating exploits for this vulnerability is quite challenging as it requires the tool to reason about the combination of arithmetic operations, interference, and the read-write semantics of the storage system in Solidity. For instance, existing tools such as ÖYENTE and MADMAX [14] will simply mark a large number of arithmetic operations as potentially vulnerable, and it turns out that most of the alarms are not exploitable.

| Vulnerability         | SMARTSCOPY | CONTRACTFUZZER |
|-----------------------|------------|----------------|
| No. | FP | FN | No. | FP | FN |
| Timestamp | 16 | 0 | 1 | 13 | 4 |
| Gasless Send | 17 | 0 | 0 | 14 | 5 |
| Bad Random | 9 | 0 | 0 | 5 | 1 |
| **TABLE V**: Comparing SMARTSCOPY against CONTRACTFUZZER |

| \(S^\dagger\)-mean | \(S^0\)-mean | \# of Benchmarks Timeout |
|---------------------|--------------|--------------------------|
| 8s | 35s | 1846 | 548 | 17454 |
| **TABLE VI**: Comparison between Summary-based \((S^\dagger)\) and Non-summary \((S^0)\). \(S^\dagger \land S^0\), \(S^\dagger - S^0\), and \(S^0 - S^\dagger\) represent number of benchmarks timeout on both, \(S^\dagger\) only, and \(S^0\) only, respectively. |
Similar to our previous experiment, we first encode the vulnerability (Section IV-B) in our language and then run our tool on the Etherscan data set. SMARTCOPY generates exploits for 32 vulnerable contracts. To verify that the exploits are effective, we setup a private blockchain using the Geth framework where we can run exploits on the vulnerable contracts. We confirmed that 20 exploits are valid. The infeasible attacks come from the incompleteness of the query as well as imprecise control flow graphs from the Vandal decompiler. Since those contracts are covered by neither the previous literature nor the media, we also sent the issues to their developers.

VIII. RELATED WORK

Smart contract security has been extensively studied in recent years. In this section we briefly discuss prior closely related work.

a) Smart Contract Analysis: Many popular security analyzers for smart contracts are based on symbolic execution. Well-known tools include Oyente, Mythril and Manticore. Their key idea is to find an execution path that satisfies a given property or assertion. While SMARTCOPY also uses symbolic evaluation to search for attack programs, our system differs from these tools in two ways. First, the prior tools adopt symbolic execution for bug finding. Our tool can be used not only for bug finding but also for exploit generation. Second, while symbolic execution is a powerful and precise technique for finding security vulnerabilities, it does not guarantee to explore all possible paths, which leads to high false negative rates as shown in Section VII-B0a. In contrast, SMARTCOPY proposes a summary-based symbolic evaluation which significantly reduces the number of paths it has to explore while maintaining the same precision.

To address the scalability and path explosion problems in symbolic execution, researchers developed sound and scalable static analyzers. Both Securify and Madmax are based on abstract interpretation, which soundly overapproximates and merges relevant execution paths to avoid path explosion. The ZEUS system takes the source code of a smart contract and a policy as inputs, and then compiles them into LLVM IRs that will be checked by an off-the-shelf verifier. The ECF system is designed to detect the DAO vulnerability. Similar to our tool, Securify also provides a query language to specify the patterns of common vulnerabilities. Unlike our tool, none of these systems can generate exploits. We could not directly compare SMARTCOPY with Securify and Zeus as their tools and benchmarks are not publicly available. However, we note that our system is complementary to existing static analyzers such as Securify: in particular, we can use Securify to filter out safe smart contracts and leverage SMARTCOPY to generate exploits for vulnerable ones.

Some systems for reasoning about smart contracts rely on formal verification. These systems prove security properties of smart contracts using existing interactive theorem provers. They typically offer strong guarantees that are crucial to smart contracts. However, unlike our system, all of them require significant manual effort to encode the security properties and the semantics of smart contracts.

Finally, projects related to reverse engineering aim to lift EVM bytecode to an intermediate representation that is easy to analyze. Although SMARTCOPY uses the IRs from Vandal, our technique is agnostic to the underlying language.

b) Automatic Exploitation: Our work is also closely related to automatic exploitation. Our work is completely based on random input generation, it is an order of magnitude slower.

IX. CONCLUSION

We presented SMARTCOPY, a tool for automatic synthesis of adversarial contracts that exploit the vulnerability of a victim smart contract under test. To make synthesis tractable, we introduced summary-based symbolic evaluation, which significantly reduces the number of paths that our tool needs to explore while maintaining the precision of the vulnerability query. Building on the summary-based symbolic evaluation, SMARTCOPY further introduces optimizations that enable it to partition the synthesis search space for parallel exploration, and to prune infeasible attack candidates earlier. We encoded common vulnerabilities of smart contracts in our language, and evaluated SMARTCOPY on the entire data set from etherscan with >25K smart contracts. As shown in our experimental evaluation, SMARTCOPY significantly outperforms state-of-the-art smart contract analyzers in terms of precision, soundness, and execution time. Moreover, running on recent smart contracts, SMARTCOPY uncovers 20 previously unknown instances with the BatchOverflow vulnerability and none of the existing tool can precisely spot the vulnerability.
