

# Making No-Fuss Compiler Fuzzing Effective

## Abstract

Developing a bug-free compiler is difficult; modern optimizing compilers are among the most complex software systems humans build. Fuzzing is one way to identify subtle compiler bugs that are hard to find with human-constructed tests. Grammar-based fuzzing, however, requires a grammar for a compiler's input language, and can miss bugs induced by code that does not actually satisfy the grammar the compiler *should* accept. Grammar-based fuzzing also seldom uses advanced modern fuzzing techniques based on coverage feedback. However, modern mutation-based fuzzers are often ineffective for testing compilers because most inputs they generate do not even come close to getting past the parsing stage of compilation. This paper introduces a technique for taking a modern mutation-based fuzzer (AFL in our case, but the method is general) and adding mutation rules, based on operators used in mutation testing, to make such fuzzing more effective. We show that adding such mutations significantly improves fuzzing effectiveness. Our approach has allowed us to report more than 100 confirmed and fixed bugs in production compilers, and found a bug in the Solidity compiler that earned a security bounty. The most important feature of our approach is that for compilers written in C, C++, Go, Rust, or another language supported by AFL, the process of fuzzing is extremely low-effort for compiler developers. They essentially build their system with fuzzer instrumentation, point the fuzzer to a set of example programs that compile without error, and examine any crashes detected.

**CCS Concepts:** • Software and its engineering → Dynamic analysis; Software testing and debugging.

**Keywords:** fuzzing, compiler development, mutation testing

## ACM Reference Format:

. 2022. Making No-Fuss Compiler Fuzzing Effective. In ., ACM, New York, NY, USA, 5 pages. <https://doi.org/10.1145/3486607.3486772>

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ACM ISBN 978-1-4503-9110-8/21/10...\$15.00

<https://doi.org/10.1145/3486607.3486772>

## 1 Introduction

Compilers are notoriously hard to test, and modern optimizing compilers tend to contain many subtle bugs. Compiler bugs can have serious consequences, including potentially the introduction of security vulnerabilities that cannot be detected by human or static analysis without knowledge of the compiler flaw [2]. The literature on compiler testing is extensive [5] and goes back to such foundational papers as McKeeman's introduction of the idea of differential testing in the context of random testing of compilers [10].

As McKeeman's work suggests, one core approach to testing compilers is based on the generation of random programs. In recent years, the Csmith [14] project is perhaps the most prominent example of this method. However, building a tool such as Csmith is a heroic effort, requiring considerable expertise and development time. Csmith itself is over 30KLOC, much of it complex and with a lengthy development history. Csmith is focused on a single, albeit extremely important, language, C. Building a tool like Csmith for a new programming language is not within the scope of most language or compiler development projects, even very prominent ones. Even for such a highly visible language/compiler project as Rust/rustc, to our knowledge there is *no* useful tool for generating random Rust programs (and none seems to be used in rustc testing). As far as we can tell, Rust is primarily (or perhaps *only*) fuzzed at the whole language level ([https://github.com/dwrensha/fuzz-rustc/blob/master/fuzz\\_target.rs](https://github.com/dwrensha/fuzz-rustc/blob/master/fuzz_target.rs)) by using a wrapper around libFuzzer, a tool with no special knowledge of Rust syntax or semantics, to randomly modify *a set of supplied Rust programs*. Similarly, the solc compiler, which essentially defines the Solidity language used to write most smart contracts for the Ethereum blockchain, is not fuzzed using a Csmith-like generator, but using methods similar to those used for Rust, again based on taking existing Solidity programs and randomly modifying them.

This approach (randomly mutating existing programs) is widely used by real-world compiler projects in part because *it is often very easy to apply*: we call it “no fuss” compiler fuzzing. Most compiler projects, even large ones, do not have a team of random testing experts available, so the construction of Csmith-like tools is out of the question. This means that the only way to generate valid programs *from scratch* is to use a tool that takes as input the *grammar* of a language and generates random outputs satisfying the grammar. However, such an approach has multiple problems. First, in many cases the programs produced by a grammar, without extensive attention to tuning the tool, will be mostly uninteresting. Csmith is successful in part because of the use of numerous heuristics to generate interesting code. Second, the grammar

of a language alone seldom provides guidance in avoiding simple errors that cause programs to be rejected without exploring interesting compiler behavior; a BNF grammar generally will not, for example, force identifiers to be defined before they are used. Third, many interesting bugs can only be exposed by programs that may not satisfy a language’s grammar, in theory, due to differences between a formal grammar and the actual parser used in a compiler, or other subtle implementation details. Salls et al. [13] elaborate this weakness in a recent paper, finding that many bugs could not be found using a grammar-based generator. Finally, a usable grammar may not be available, especially as the tools will expect a grammar in a particular format, and may add restrictions on the structure of the grammar. In the early stages, many programming language projects lack a stable, well-defined grammar in any formal, standalone, notation. An ad-hoc “grammar” used by the compiler implementation may be the only grammar around. Thus, while grammar-based compiler testing has sometimes been extremely successful (e.g., the LangFuzz [7] approach), few compilers are actually extensively tested using purely grammar-based tools.

Therefore, many projects rely on an approach we will define in more detail below, which uses off-the-shelf *fuzzing* tools, originally designed to find security vulnerabilities in programs, to modify existing inputs (programs) rather than generate programs from scratch. This approach has found many subtle compiler bugs, but suffers from two major drawbacks:

1. First, in most cases the methods used by such programs to modify (mutate) inputs tend to take code that exercises interesting compiler behavior, and transform it into code that is rejected in the early stages of parsing. That is, in most cases, general-purpose fuzzers tend to take code and turn it into “non-code.” This makes such fuzzing inefficient, and makes it almost impossible for it to find bugs requiring many subtle modifications of corpus programs.
2. Second, when such fuzzers do find bugs, the bugs are often found in particularly un-humanlike inputs, such as code containing non-printable bytes. Bugs are often at the “crash the parser” level rather than deeper semantic levels of the compiler.

Combined together, these problems make most compiler fuzzing performed in practice, even on major projects, both inefficient in terms of finding bugs and perhaps prone to find bugs that are not the most important and interesting compiler bugs.

Given that this kind of “no-fuss” fuzzing is the *only* option available in practice to small compiler projects that cannot devote resources to tuning a grammar-based fuzzer (or perhaps even supporting an always-up-to-date grammar), improving the effectiveness of such compiler fuzzing is an obvious way to practically improve compiler testing. Ideally,

such improvements would not require *any* additional effort or change the workflow of existing compiler fuzzing setups (other than changing the tool to be used).

This paper proposes one such improvement, based on changing the way in which general-purpose fuzzers modify (mutate) inputs. We augment the set of changes made by such tools with a large number of modifications drawn from the domain of *mutation testing*, which only modifies code in ways likely to preserve desirable properties, such as the ability to get through a parser. We evaluate our technique on several real-world compilers, and show that it dramatically improves the mean number of distinct compiler bugs detected, and moreover produces a much larger set of distinct, successfully compiling, inputs that explore compiler behavior. As a result of our approach, which is available as an easy-to-use tool based on the widely used AFL fuzzer, we have reported more than 100 bugs in important real-world compilers, the great majority of which have been confirmed and fixed, and received a bug bounty for our efforts. In the longest-running campaign, that targeting the solc compiler for Solidity code, we were the first to report a very large number of serious bugs, despite continuous, extensive fuzzing using un-modified AFL performed by the compiler developers and external contributors, over the same time frame.

## 2 Mutation-Testing-Based Compiler Fuzzing

### 2.1 Mutation-Based Fuzzing

One use of the term “mutation” appears in the context of *mutation-based* fuzzing [9], the primary random testing approach used by many compiler projects, as discussed above. Again, we note that there are two basic kinds of compiler testing based on the generation of random inputs to a compiler. One, in recent years paradigmatically expressed in the Csmith tool [14], works by using a grammar and/or deep knowledge of the language accepted by the compiler, to generate programs to test the compiler. This is sometimes called *generative* fuzzing. Generative fuzzing can be very effective, but often requires expert tuning of a large, sophisticated tool, and at minimum requires having a suitable usable grammar for the language of the compiler. In practice, many compiler projects do not employ generative fuzzing for practical reasons.

A second approach, and the only approach widely used in many major compiler projects, is to use an off-the-shelf fuzzer, such as is used to find security vulnerabilities (e.g., the ubiquitous American Fuzzy Lop (afl) <https://github.com/google/AFL>) or libFuzzer, and a *corpus* of example programs, such as the set of regression tests for the compiler or a set of real-world programs. A fuzzer such as AFL operates by executing the program under test (here, the compiler) on inputs (initially those in the corpus), using instrumentation to determine code coverage in the compiler for each executed

input. The fuzzer then takes inputs that look interesting and adds them to a *queue*. The basic loop is then to take some input from the queue, *mutate* it by making some essentially random change (e.g., flipping a single bit, or removing a random chunk of bytes), execute the new, mutated input under instrumentation, and add the new input to the queue if it seems “interesting” — typically, if it hits some kind of coverage target that has not previously been hit. The details of selecting inputs from the queue and determining how to mutate an input vary widely, and improving the effectiveness of this basic approach has been a major topic of recent software testing and security research. However, the basic strategy usually still fits into a simple basic model:

1. Select an input from the queue.
2. Mutate that input in order to obtain a new input.
3. Execute the new input, and if it is deemed interesting, add it to the queue.
4. Go back to the first step.

Any inputs that crash the compiler in step 3 are reported to the user. Using such a fuzzer is often extremely easy, involving no more work than 1) building the compiler with special instrumentation and 2) finding a set of initial programs to use as a corpus. Even compiling with instrumentation can be optional; some fuzzers (including AFL) can use QEMU to fuzz arbitrary binaries. However, for compilers, it is usually best if possible to rebuild the compiler, since QEMU-based execution is much slower, and compilers are slow enough to seriously degrade fuzzing throughput.

Our work focuses on improving step 2 of this process, in a way that is agnostic to how the details of the other aspects of fuzzing are implemented. In particular, the problem with most approaches to mutation in the literature, for compiler fuzzing, is that changes such as byte-level-transformations almost always take compiling programs that exercise interesting compiler behavior, and transform them into programs that don’t make it past early stages of parsing. Alternative approaches to what are called “havoc”-style mutations tend to involve solving constraints or following taint, which in the case of compilers tends to be ineffective, since the relationships to be preserved are quite complex, and implemented in complex code. A second common approach, providing a *dictionary* of meaningful byte sequences in a language, is both burdensome on compiler developers (though less so than providing a full grammar), and limited in effectiveness: a dictionary cannot, for example, help the fuzzer delete meaningful sub-units of code, such as statements or blocks.

We propose a novel way to produce a much larger number of useful, interesting mutations for source code, without paying an analytical price that makes fuzzing practically infeasible for compilers, and without requiring *any* additional effort on the part of compiler developers.

## 2.2 Mutation Testing

A different use of the term “mutation” appears in the field of mutation testing. Mutation testing [4, 8, 11] is an approach to evaluating and improving software tests that works by introducing small syntactic changes into a program, under the assumption that if the original program was correct, then a program with slightly different semantics will be incorrect, and should be flagged as such by effective tests. Mutation testing is now widely used in software testing research, and is used to varying degrees in industry at-scale and for especially critical software development [1, 3, 12].

A mutation testing approach is defined by a set of mutation operations. Such operations vary widely in the literature, though a few, such as deleting a small portion of code (such as a statement) or replacing arithmetic and relational operations (e.g., changing `+` to `-` or `==` to `<=`), are very widely used. Most mutation testing tools parse the code to be mutated, and many do not work on code that does not parse. However, recently there has been a proposal to perform mutation testing using truly purely syntactic operations, defined by a set of regular expressions implementation operations [6]. Rather than taking a program, per se, this approach simply takes “code-like” text and produces a set of variants that, if the original text is compiling source code, will include most common mutations. The essence of this approach to mutation testing, which can be applied to “any language,” is essentially a transformation from arbitrary bytes to arbitrary bytes that, if the original bytes are “code-like” will tend to preserve the property of being “code-like.”

## 2.3 Combining Both Forms of Mutation

Our approach is, in essence, simple. We add a set of mutations to the repertoire of a mutation-based fuzzer, for use in compiler fuzzing. These mutations are either traditional mutation operators from the mutation testing domain or inspired by traditional mutation operators, but with changes made to satisfy the needs of fuzzing. The key point is that, unlike most changes made by mutation-based fuzzers, these mutations are likely to take interesting code inputs and preserve the property, e.g., that the input will get through a parser or trigger interesting optimizations. The tendency to preserve such properties is natural, since the basis of mutation testing is to take an existing program and produce a set of new, similar programs, by applying mutation operators. If most mutation operators tended to produce uninteresting code that doesn’t even compile, mutation testing would not be of use to anyone. Moreover, because our approach is based on the idea of a “universal” mutation tool [6], the mutation operators used are generally language-agnostic, and useful for fuzzing any programming language, or at least a wide variety of real-world languages.



## 2.4 Limitations

The most important limitation for the mutation-testing-based approach is that if compiler *crashes* are mostly uninteresting, fuzzing of this kind will probably not be very useful. This applies, of course, to all AFL-style fuzzing, not just to fuzzing using the technique proposed in this paper. For example, C and C++ include a large variety of undefined behaviors. Code that crashes a C or C++ compiler, but that includes (unusual) undefined behavior may well be ignored by developers. Csmith [14] devotes a great deal of effort to avoiding generating code that falls outside the “interesting” part of the language. On the other hand, many languages more recent than C and C++ attempt to provide a more “total” language where, while a program may be considered absurd by a human, fewer (or no) programs are undefined in the sense that C and C++ use the term. For example, smart contract languages such as those studied in this paper, generally aim to make all programs that compile well-defined, or at least minimize the problem to more manageable cases such as order of evaluation of sub-expressions. Similarly, Rust code without use of `unsafe` should not crash the compiler, and any such crashes indicate possible bugs in the Rust compiler or type system. For most more recent languages, and some older languages such as Java, a program that crashes the compiler is, in general, likely of interest to compiler developers. However, the proposed technique will be much more limited in effectiveness for C and C++ compilers.

## 3 Implementation and Example Operations

### 3.1 Fast or Smart?

#### 3.1.1 Fast String-level Approximation of Mutation Operators.

#### 3.1.2 Parser Parser Combinator-Based Intelligent Mutation.

## 4 Evaluation

### 4.1 Setup

**Corpus.** For solidity, all `.sol` files in `test/libsolidity`. For Move, all `.diem` files in the repository. For Fe, **all .fe files in repository**. AFL starts of preprocessing inputs based on coverage and ignores uninteresting ones. **say how many for each proj**

For the template splicing technique, we start off with a noop input and gradually generate (template, fragment) pairs, synthesized on-demand. After generating pairs, we removed all large inputs in the (template, fragment) corpus ( $> 4\text{KB}$ ). **say how many of these**.

## 5 Related Work

Research on compiler testing, as noted in the introduction, has been an important subfield overlapping compiler development and design and software engineering and testing, for many years. Chen et al. summarize much of this work in a recent survey [5].

To our knowledge, very little work has appeared targeting the problem this paper addresses: improving the ability of general-purpose fuzzers to find (interesting) bugs in compilers. The recent work of Salls et al. [13], however, specifically aims to improve general-purpose fuzzer performance on compilers and interpreters. Their approach, which they call “token-level fuzzing” essentially produces a hybrid level in between grammar-based generation and “byte-level” mutation-based fuzzing. The core of their idea is to replace the largely byte-level mutations of AFL etc. with mutations at the *token* level of a grammar. They summarize the idea as “valid tokens should be replaced with valid tokens” [13]. In a sense, this extends the idea of using a dictionary, but with important changes: token-level fuzzing *only* applies token-level, not byte-level mutations, but also adds the composition of multiple token additions and substitutions to the set of single-step mutations. Token-level fuzzing is an attractive and useful idea, somewhat orthogonal to our approach. However, unlike our approach, token-level fuzzing does not apply AFL’s havoc operations, so some bugs are simply not possible to find using token-level fuzzing (e.g., ones involving injecting unprintable characters in strings). In this sense, token-level fuzzing has some of the limitations of grammar-based generation. Token-level fuzzing also provides little help to a fuzzer in deleting large chunks of code, since this often would require a very large number of token operations, though the approach does include a way to copy statements from one input to another. Finally, token-level fuzzing requires using a lexer to find all tokens in input seeds, and if tokens not in those seeds would be useful, developers must provide any additional tokens. This requires modifying the fuzzing workflow to add token pre-processing, and is no longer strictly *no-fuss*.

## 6 Conclusions

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Project	Configuration	Unique Bugs			Avg Execs (Millions)	Avg Paths (K)	Avg Bitmap Cvg (%)
		Avg	Min	Max			
Solidity	ground-truth	3.69	1	6	35.8	12.0	54.34
	text-mutation	8.19	7	11	30.3	14.3	55.65
	splice-mutation	9.47	7	13	16.0	16.8	57.33
Move	ground-truth	????	?	??	56.9	4.9	63.23
	text-mutation	????	?	??	61.2	6.0	62.27
	splice-mutation	????	?	??	7.2	5.0	63.18
Zig	ground-truth	????	?	??	????	???	?????
	text-mutation	????	?	??	????	???	?????
	splice-mutation	????	?	??	????	???	?????

**Table 1.** Main results. We fuzzed each project for 16 trials (24 hours per trial) in three different configurations: ground-truth, text-mutation, and splice-mutation. ground-truth is stock AFL. text-mutation applies mutation operators (textual find-replace patterns) with a probability of 75% on every fuzzed input. Sock AFL manipulates the input with the remainder, 25% of the time. splice-mutation is a hybrid approach that (1) applies mutation operators as in text-mutation with probability 33%; (2) synthesizes a syntax-aware input with template (splice) 33% of the time, and (3) uses stock AFL for the remaining 34%. **TODO: summarize results once flush.**

Computer Science.

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