An interleaving approach to combinatorial testing and failure-inducing interaction identification

Xintao Niu, Changhai Nie, *Member, IEEE,* Hareton Leung, *Member, IEEE,* Jeff Y. Lei, *Member, IEEE,* Xiaoyin Wang, *Member, IEEE,* Jiaxi Xu and Yan Wang

Abstract

Combinatorial testing(CT) seeks to detect potential faults caused by various interactions of factors that can influence the software systems. When applying CT, it is a common practice to first generate a set of test cases to cover each possible interaction and then to identify the failure-inducing interaction after a failure is detected. Although this conventional procedure is simple and forthright, we conjecture that it is not the ideal choice in practice. This is because 1) testers desire to identify the root cause of failures before all the needed test cases are generated and executed 2) the early identified failure-inducing interactions can guide the remaining test case generation so that many unnecessary and invalid test cases can be avoided. For these reasons, we propose a novel CT framework that allows both generation and identification process to interact with each other. As a result, both generation and identification stages will be done more effectively and efficiently. We conducted a series of empirical studies on several

Xintao Niu and Changhai Nie are with the State Key Laboratory for Novel Software Technology, Nanjing University, China, 210023.
E-mail: niuxintao@gmail.com, changhainie@nju.edu.cn

Hareton Leung is with Department of computing, Hong Kong Polytechnic University, Kowloon, Hong Kong.
E-mail: hareton.leung@polyu.edu.hk

Jeff Y. Lei is with Department of Computer Science and Engineering, The University of Texas at Arlington, Arlington, Texas.
E-mail: ylei@cse.uta.edu

Xiaoyin Wang is with Department of Computer Science, University of Texas at San Antonio.
E-mail: Xiaoyin.Wang@utsa.edu

Jiaxi Xu and Yan Wang are with School of Information Engineering, Nanjing Xiaozhuang University.
E-mail: xujiaxi@njxzc.edu.cn, wangyan@njxzc.edu.cn

Manuscript received April 19, 2005; revised September 17, 2014.

open-source software, the results of which show that our framework can identify the failure-inducing interactions more quickly than traditional approaches while requiring fewer test cases.

Index Terms

Software Testing, Combinatorial Testing, Covering Array, Failure-inducing interactions

I. INTRODUCTION

Modern software is becoming more and more complex. To test such software is challenging, as the candidate factors that can influence the system's behaviour, e.g., configuration options, system inputs, message events, are enormous. Even worse, the interactions between these factors can also crash the system, e.g., the incompatibility problems. In consideration of the scale of the industrial software, to test all the possible interactions of all the factors (we call them the interaction space) is not feasible, and even if it is possible, it is resource-inefficient to test all the interactions.

Many empirical studies show that, in real software systems, the effective interaction space, i.e., targeting fault detection, makes up only a small proportion of the overall interaction space [1], [2]. Further, the number of factors involved in these effective interactions is relatively small, of which 4 to 6 is usually the upper bounds [1]. With this observation, applying Combinatorial testing(CT) in practice is appealing, as it is proven to be effective to detect the interaction faults in the system.

CT tests software with an elaborate test suite which checks all the required parameter value combinations. A typical CT life-cycle is shown in Figure 1, which contains four main testing stages. At the very beginning of the testing, engineers should extract the specific model of the software under test (SUT). In detail, they should identify the factors, such as user inputs, and configure options, which could affect the system's behavior. Further effort is required to figure out the constraints and dependencies among each factor and corresponding values for valid testing. After the modeling stage, a set of test cases should be generated and executed to expose the potential faults in the system. In CT, each test case is a set of assignments of all the factors in the test model. Thus, when such a test case is executed, all the interactions contained in the test case are deemed to be checked. The main target of this stage is to design a relatively small set of test cases to achieve some specific coverage. The third testing stage in this cycle is the fault localization, which is responsible for identifying the failure-inducing interactions. To characterize the failure-inducing interactions of corresponding factors and values is important for future bug fixing, as it will reduce the scope of suspicious code to be inspected. The last testing stage of CT is the evaluation. In this stage, testers will assess the quality of the previously conducted testing tasks. If the assessment result shows that the previous testing process does not fulfill the testing requirement, some testing stages should be improved, and sometimes, may even need to be re-conducted.

Although this conventional CT framework is simple and straightforward, in terms of the test case generation and fault localization stages, we conjecture that first-generation-then-identification is not the proper choice in practice. The reasons are twofold. First, it is not realistic for developers to wait for all the needed test cases are generated before they can diagnose and fix the failures that have been detected [3]; Second, and the most important, utilizing the early determined failure-inducing interactions can guide the following test case generations, such that many unnecessary and invalid test cases can be avoided. For this we get the key idea of this paper: *Generation and Fault Localization process should be interleaving.*

Based on the idea, we propose a new CT framework, which integrates these two stages together instead of dividing the generation and identification into two independent stages. Specifically, we first execute one or more tests until a failure is observed. Next, we immediately turn to the fault localization stage, i.e., identify failure-inducing interactions for that failure. These failure-inducing interactions are used to update the current coverage. In particular, interactions that are related to these failure-inducing interactions do not need to be covered in future executions. Then, we continue to perform regular combinatorial testing.

We remodel the test case generation and failure-inducing interactions identification modules to make them better adapt to this new framework. Specifically, for the generation part of our framework, we augment it by forbidding the appearance of test cases which contain the identified failure-inducing interactions. This is because those test cases containing a failure-inducing interaction will fail as expected so that it does not contribute for additional failure detection. For the failure-inducing identification module, we augment it to achieve higher coverage. More specifically, we refine the additional test case generation in this module, so that it can not only help to identify the failure-inducing interactions but also cover as many uncovered interactions as possible. As a result, our new CT framework is efficient at test case generation and MFS identification.

Our new framework has strict requirements in the accuracy of the identified failure-inducing interactions. This is mainly because it forbids the appearance of test cases which contain the identified interactions. Hence, if these interactions are not failure-inducing, they will never be covered again, and adequate testing will not be reached. To improve the accuracy of the failure-inducing interaction identification results, we propose a novel feedback checking mechanism which aims at checking whether the interactions identified by our framework are accurate or not. Particularly, if these interactions do not pass the checking process, we will restart the failure-inducing identification module to re-identify other interactions.

We conducted a series of empirical studies on 5 open-source software and several synthetic software to evaluate our new framework. These studies start with two comparisons. The first one is to compare our new interleaving framework with the traditional sequential framework, which first generates a complete set of test cases and then performs the fault localization. The second one is to compare our framework with the feedback-driven CT [4], [5], which also adapts an iterative framework to generate test cases and identifying failure-inducing interactions, but to address the problem of inadequate testing. We also evaluated the sensitivities of these approaches with respect to the number of the options of the system under test and the number of failure-inducing interactions contained in it. Besides, we discussed the negative influences of non-deterministic failures and the issue of a system with no option value that is irrelevant to any failure-inducing interaction (called the non-safe value issue). The main results of these experiments are summarized as follows:

1) Compared to the other approaches, our new interleaving framework obtained better failure-inducing interaction identification results in most cases (both empirical studies on real software and empirical studies on synthetic software). The new interleaving framework also decreased the number of generated test cases when compared with the traditional sequential framework in most cases, and it obtained a good result at the reduction of masking effects caused by different failure-inducing interactions even when compared to the feedback-driven CT which focuses on the reduction of masking effects.
2) Feedback-driven CT generated the smallest number of test cases in most cases, especially when the number of options of the system under testing is large, it also obtained a good result at the reduction of masking effects. As for traditional sequential framework, its results of these experiments lay in between those of the other two approaches in most cases.
3) The novel feedback checking mechanism benefits our new interleaving framework a lot, especially on the improvement of the accurateness of failure-inducing interaction identification and the coverage of interactions to be covered.

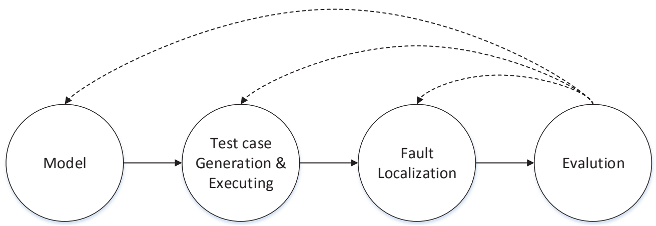


Fig. 1. The life cycle of CT

4) Increasing the number of failure-inducing interactions has a negative effect on all these approaches when considering the accurateness of failure-inducing interaction identification.
5) The non-deterministic failures also have a negative effect on these approaches, especially when the possibility of the appearance of failures ranges from 0.3 to 0.8. One potential solution is to increase the redundancy of test case execution.
6) Similar to the issue caused by a large number of failure-inducing interactions, the non-safe value issue also has a negative effect on all these three approaches, but the feedback mechanism can help our new interleaving framework to alleviate this negative effect to some extent.

The main contributions of this paper are as follows.

1) We propose a new CT framework which combines the test case generation and fault localization more closely.
2) We augment the traditional CT test case generation and failure-inducing interactions identification process to make them adapt to the new framework.
3) We give a novel feedback checking mechanism which can check whether the interaction identified by our approach is failure-inducing or not, and it significantly improves the accuracy of the results of the failure-inducing interaction identification approach.
4) We perform a series of comparisons with traditional CT and Feedback-driven CT. The results of the empirical studies are discussed.

The rest of the paper is organised as follows: Section II presents the preliminary background of CT. Section III presents a motivating example. Section IV describes our new framework and a simple case study is also given. Section V presents the empirical studies and discusses the results. Section VI shows the related works. Section VII concludes the paper and proposes some further work.

II. Background

This section presents some definitions and propositions to give a formal model for CT.

Assume that the Software Under Test (SUT) is influenced by *n* parameters, and each parameter p_i can take the values from the finite set V_i, $|V_i|$ = a_i (i = 1,2,..n). The definitions below are originally defined in [6].

Definition 1: A *test case* of the SUT is a tuple of *n* values, one for each parameter of the SUT. It is denoted as (v_1, v_2,...,v_n), where $v_1 \in V_1$, $v_2 \in V_2$ ... $v_n \in V_n$.

In practice, these parameters in the test case can represent many factors, such as input variables, run-time options, building options or various combination of them. We need to execute the SUT with these test cases to ensure the correctness of the behaviour of the SUT.

We consider any abnormally executing test case as a *fault*. It can be a thrown exception, a compilation error, an assertion failure, a constraint violation, etc. When faults are triggered by some test cases, it is desired to figure out the cause of these faults.

Definition 2: For the SUT, the *n*-tuple (-,v_{n_1},...,v_{n_k},...)is called a *k*-degree *schema* ($0 < k \leq n$) when some k parameters have fixed values and other irrelevant parameters are represented as "-".

In effect, a test case itself is a k-degree *schema* when k = n. Furthermore, if a test case contains a *schema*, i.e., every fixed value in the schema is in this test case, we say this test case *contains* the *schema*.
Note that the schema is a formal description of the interaction between parameter values we discussed before.

Definition 3: Let c_l be an *l*-degree schema, c_m be an *m*-degree schema in SUT and $l < m$. If all the fixed parameter values in c_l are also in c_m, then c_m *subsumes* c_l. In this case, we can also say that c_l is a *sub-schema* of c_m and c_m is a *super-schema* of c_l, which can be denoted as $c_l \prec c_m$.

For example, the 2-degree schema (-, 4, 4, -) is a sub-schema of the 3-degree schema (-, 4, 4, 5), that is, (-,4,4,-) $\prec$ (-,4,4,5).

Definition 4: If all test cases that contain a schema, say c, trigger a particular fault, say F, then we call this schema c the *faulty schema* for F. Additionally, if none of sub-schema of c is the *faulty schema* for F, we then call the schema c the *minimal failure-causing schema (MFS)* [6] for F.

Note that MFS is identical to the failure-inducing interaction discussed previously. In this paper, the terms *failure-inducing interactions* and *MFS* are used interchangeably. Figuring the MFS out helps to identify the root cause of a failure and thus facilitate the debugging process.

A. CT Test Case Generation

When applying CT, the most important work is to determine whether the SUT suffers from the interaction faults or not, i.e., to detect the existence of the MFS. Rather than impractically executing exhaustive test cases, CT commonly designs a relatively small set of test cases to cover all the schemas with the degree no more than a prior fixed number, t. Such a set of test cases is called the *covering array*. If some test cases in the covering array failed in execution, then the interaction faults are considered to be detected. Let us formally define the covering array.

Definition 5: $MCA(N; t, n, (a_1, a_2, ..., a_n))$ is a t-way *covering array* in the form of $N \times n$ table, where each row represents a *test case* and each column represents a parameter. For any t columns, each possible t-degree interaction of the t parameters (schema) must appear at least once. When $a_1 = a_2 = ... = a_n = v$, a t-way covering array can be denoted as $CA(N; t, n, v)$.

TABLE I

A COVERING ARRAY

ID	**Test case**			
t_1	0	0	0	0
t_2	0	1	1	1
t_3	1	0	1	1
t_4	1	1	0	1
t_5	1	1	1	0

For example, Table I shows a 2-way covering array CA(5; 2, 4, 2) for the SUT with 4 boolean parameters. For any two columns, any 2-degree schema is covered. Covering array has proven to be effective in detecting the failures caused by interactions of parameters of the SUT. Many existing algorithms focus on constructing covering arrays such that the number of test cases, i.e., N, can be as small as possible. In general, most of these studies can be classified into three categories according to the construction strategy of the covering array [7]:

1) One test case one time: This strategy repeats generating one test case as one row of the covering array and counting the covered schemas achieved until all schemas are covered [8]–[10].

2) A set of test cases one time: This strategy generates a set of test cases at each iteration. By mutating the values of some parameters of some test cases in this test set, it focuses on optimizing the coverage. If the coverage is finally satisfied, it will reduce the size of the set to see if fewer test cases can still fulfill the coverage. Otherwise, it will increase the size of the test set to cover all the schemas [11], [12].

3) IPO-like style: This strategy differentiates from the previous two strategies in that it does not firstly generate complete test cases [13]. Instead, it first focuses on assigning values to some part of the factors or parameters to cover the schemas that are related to these factors and then fills up the remaining part to form complete test cases.

In this paper, we focus on the first strategy: One test case one time as it immediately gets a complete test case so that the testers can execute and diagnose in the early stage. As we will see later, with respect to the MFS identification, this strategy is the most flexible and efficient one compared with the other two strategies.

B. Identify the failure-inducing interactions

To detect the existence of MFS in the SUT is still far from figuring out the root cause of the failure [14]–[16], as we do not know exactly which schemas in the failed test cases should be responsible for the failure. For example, if t_1 in Table I failed during testing, there are six 2-degree candidate failure-inducing schemas, which are (0, 0, -, -), (0, -, 0, -), (0, -, -, 0) , (-, 0, 0, -), (-, 0, -, 0), (-, -, 0, 0), respectively. Without additional information, it is difficult to figure out the specific schemas in this suspicious set that caused the failure. Considering that the failure can be triggered by schemas with other degrees, e.g., (0, -, -, -) or (0, 0, 0, -), the problem of MFS identification becomes more complicated.

In fact, for a failing test case $(v_1, v_2, ..., v_n)$, there can be at most $2^n - 1$ possible schemas for the MFS. Hence, more test cases should be generated to identify the MFS. In CT, the main work in fault localization is to identify the failure-inducing interactions. Further works of fault localization such as isolating the specific defective source code will not be discussed.

A typical MFS identification process is shown in Table II. This example assumes the SUT has 3 parameters, each of which can take on 2 values, and the test case (1, 1, 1) fails. Then in Table II, as test case *t* failed, we mutate one factor of test case *t* at one time to generate new

TABLE II
OFOT EXAMPLE

Original test case				**Outcome**
t	1	1	1	Fail
Additional test cases				
t_1	0	1	1	Pass
t_2	1	0	1	Fail
t_3	1	1	0	Fail

test cases: t_1 – t_3. It turns out that test case t_1 passed, which indicates that this test case breaks the MFS in the original test case *t*. So (1,-,-) should be a failure-causing factor. Besides, since other mutating test cases all failed, there is no any other failure-inducing factor that is broken. Therefore, the MFS in *t* is (1,-,-).

This identification process mutates one factor of the original test case at a time to generate extra test cases. Then according to the outcome of the test cases execution result, it will identify the MFS of the original failing test cases. It is called the OFOT method [6], which is a well-known MFS identification method in CT. In this paper, we will focus on this identification method. It should be noted that the following proposed CT framework can be easily applied to other MFS identification methods.

Note that all the existing MFS identification approaches just give approximation solutions for MFS identification. In fact, to exactly identify the MFS (without any assumptions), it needs an exponential number of test cases [17], which is impossible in practice. Hence, all the existing MFS identification approaches, as well as the approach we will propose in this paper, need additional assumptions or just identify the likely failure-inducing interactions. For example, the OFOT approach is based on the following two assumptions:

Assumption 1: The execution result of a test case is deterministic.

This assumption is a common assumption of CT [17]–[19]. It indicates that the outcome of executing a test case is reproducible and will not be affected by some random events.

Assumption 2: Given a failing test case t, when we identify the MFS in t, any newly generated test case will not introduce new MFS that is not in t.

The second assumption is identical to the assumption proposed in [15], [16], [18], which is called the safe value assumption. Based on this assumption, when the additional test case generated by OFOT fails, e.g., t_2 in Table II, we can determine that the additional test case contains the same MFS in the original failing test case, e.g., t in Table II.

Note that in practice, these assumptions do not always hold. Hence, the approaches proposed later in this paper actually can only identify approximate MFS instead of the real MFS. We will discuss the impacts of these assumptions on the approaches proposed in this paper in the experiments. **Additionally, without special emphasis (for example, "the real MFS"), all the sentences contained such as "the MFS identified by some approaches" actually mean that"the approximate MFS obtained by these approaches".**

III. Motivating example

In this section, a motivating example is presented to show how traditional CT works as well as its limitations. This example is derived from our attempt to test a real-world software–HSQLDB, which is a pure-java relational database engine with large and complex configuration space. To extract and manipulate valid configurations of this highly-configurable system is important, as different configurations can result in significantly different behaviours of the system [20]–[22] (HSQLDB normally works under some proper configurations, but crashes or throws exceptions under some other configurations).

Considering the large configuration space of HSQLDB, we first utilized CT to generate a relatively small set of test cases. Each of them is actually a set of specific assignments to those options we cared [1]. For each configuration, HSQLDB is tested by sending prepared SQL commands. We recorded the output of each run, but unfortunately, about half of them produced exceptions or warnings. Following the schedule of traditional CT, we started the identification process to isolate the failure-inducing option interactions in those failing configurations. Each failing configuration should be individually handled, in principle, as there may exist distinct failure-inducing option interactions among them. However, this successive identification process, although appealing, was hardly ever followed for this case study. This is because there are too many failing configurations and most of them contain the same failure-inducing option interactions, based on which the MFS identification process is wasteful and inefficient.

For the sake of convenience, we provide a highly simplified scenario to illustrate the problems we encountered. Consider four options in HSQLDB – *Server type*, *Scroll Type*, *Parameterised*

[1]More details in: http://gist.nju.edu.cn/doc/ict/

SQL and *Statement Type*. The possible values each option can take on are shown in Table III. Based on the report in the bug tracker of HSQLDB [2], an *incompatible exception* will be triggered if a *parameterised SQL* is executed as a *prepared statement* by HSQLDB. Hence, when option *Parameterised SQL* is set to be *true* and *Statement type* to be *preparedStatement*, our testing will crash. Besides this failure, there exists another option value which can also crash this database engine. It is when *Scroll Type* is assigned to *sensitive*, as this feature is not supported by this version of HSQLDB [3]. Without this knowledge at prior, we need to detect and isolate these two failure-inducing option interactions by CT.

TABLE III
HIGHLY SIMPLIFIED CONFIGURATION OF HSQLDB

	Option	**Values**
o_1	Server type	server, web-server, in-process
o_2	Scroll type	sensitive,insensitive, forward-only
o_3	Parameterised SQL	true, false
o_4	Statement Type	statement, preparedStatement

Table IV illustrates the process of traditional CT on this subject. For simplicity of notation, we use consecutive symbols 0, 1, 2 to represent different values of each option (For *Parameterised SQL* and *Statement type*, the symbol is up to 1). According to Table IV, traditional CT first generated and executed the 2-way covering array (t_1 – t_9 in the *generation* part). Note that this covering array covered all the 2-degree schemas for the SUT.

After testing the 9 test cases (t_1 to t_9), we found t_1, t_4, and t_7 failed. It is then desired to respectively identify the MFS of these failing test cases. For t_1, the OFOT method is used to generate four additional test cases (t_{10} – t_{13}), and the MFS (-, 0, -, -) of t_1 is identified (*Scroll Type* is assigned to *sensitive*, respectively). This is because only when changing the second factor of t_1, the additionally generated test case will pass. Then the same process is applied to t_4 and t_7. Finally, we found that the MFS of t_4 is (-, -, -, -), indicating that OFOT failed to determine the MFS (this will be discussed later), and the MFS of t_7 is the same as t_1. Totally, for detecting and identifying the MFS in this example, we generated 12 additional test cases (marked with stars).

[2]For details, see: http://sourceforge.net/p/hsqldb/bugs/1173/

[3]For details, see: http://hsqldb.org/doc/guide/guide.html

TABLE IV

SEQUENTIAL CT PROCESS

Generation (Execution)

	test case	o_1	o_2	o_3	o_4	Outcome
	t_1	0	**0**	0	0	Fail
	t_2	0	1	1	1	Pass
	t_3	0	2	1	0	Pass
	t_4	1	**0**	**0**	**1**	Fail
	t_5	1	1	0	0	Pass
	t_6	1	2	1	1	Pass
	t_7	2	**0**	1	1	Fail
	t_8	2	1	0	0	Pass
	t_9	2	2	0	0	Pass

Identification

t_1 (0,0,0,0)	t_{10}*	1	0	0	0	Fail
	t_{11}*	0	1	0	0	Pass
	t_{12}*	0	0	1	0	Fail
	t_{13}*	0	0	0	1	Fail
	MFS	**(-, 0, -, -)**				
t_4 (1,0,0,1)	t_{14}*	2	**0**	**0**	**1**	Fail
	t_{15}*	1	1	**0**	**1**	Fail
	t_{16}*	1	**0**	1	1	Fail
	t_{17}*	1	**0**	0	0	Fail
	MFS	**(-, -, -, -)**				
t_7 (2,0,1,1)	t_{18}*	0	0	1	1	Fail
	t_{19}*	2	1	1	1	Pass
	t_{20}*	2	0	0	1	Fail
	t_{21}*	2	0	1	0	Fail
	MFS	**(-, 0, -, -)**				

We refer to such traditional life-cycle as ***Sequential CT*** (SCT). However, we believe this may not be the best choice in practice. The first reason is that the engineers normally do not want to wait for fault localization after all the test cases are executed. The early bug fixing is appealing and can give the engineers confidence to keep on improving the quality of the software. The second reason, which is also more important, is such life-cycle can generate many redundant and unnecessary test cases, which negatively impacted both test case generation and

MFS identification. The most obvious negative effect in this example is that we did not identify the expected failure-inducing interaction (-, -, 0, 1), which corresponds to option *Parameterised SQL* being set to *true* and *Statement Type* being set to *preparedStatement*. More shortcomings of the sequential CT are discussed in the following subsections.

A. Redundant test cases

The first shortcoming of SCT is that it may generate redundant test cases so that some of them do not cover as many uncovered schemas as possible. As a consequence, SCT may generate more test cases than actually needed. This can be reflected in the following two aspects:

1) The test cases generated in the identification stage can also contribute some coverage, i.e., the schemas appear in the passing test cases in the identification stage may have already been covered in the test case generation stage. For example, when we identify the MFS of t_1 in Table IV, the schema (0, 1, -, -) contained in the extra passing test case t_{11} – (0, 1, 0, 0) has already appeared in the passing test case t_2 – (0, 1, 1, 1). In other words, if we first identify the MFS of t_1, then t_2 is not a good choice as it does not cover as many 2-degree schemas as possible. For example, (1, 1, 1, 1) is better than this test case at contributing more coverage.

2)The identified MFS should not appear in the following generated test cases. This is because according to the definition of MFS, each test case containing this schema will trigger a failure, i.e., to generate and execute more than one test case contained the MFS makes no sense for the failure detection. Taking the example in Table IV, after identifying the MFS – (-, 0, -, -) of t_1, we should not generate the test case t_4 and t_7. This is because they also contain the identified MFS (-, 0, -, -), which will result in them failing as expected. Since the expected failure caused by MFS (-, 0, -, -) makes t_7 and t_9 superfluous for error-detection, the additional test cases (t_{14} to t_{21}) generated for identifying the MFS in t_4 and t_7 are also not necessary.

B. Multiple MFS in the same test case

When there are multiple MFS in the same test case, MFS identification will be negatively affected. Particularly, some MFS identification approaches cannot identify a valid schema in this case. For example, there are two MFS in t_4 in Table IV, i.e., (-, 0, -, -) and (-, -, 0, 1) (shown in bold). When we use OFOT method, we found all the additionally generated test cases (t_{14} to t_{17}) failed. These outcomes give OFOT a false indication that all the failure-inducing factors are not broken by mutating those four parameter values. As a result, OFOT cannot determine which schemas are MFS, which is denoted as (-, -, -, -).

The reason why OFOT cannot properly work is that this approach can only break one MFS at a time. If there are multiple MFS in the same test case, the additionally generated test cases will always fail as they contain other non-broken MFS (see bold parts of t_{14} to t_{17}). Some approaches have been proposed to handle this problem, but they either cannot handle multiple MFS that have overlapping parts [18], or consume too many additionally generated test cases [17], [23]. So in practice, to make MFS identification more effective and efficient, we need to avoid the appearance of multiple MFS in the same test case.

SCT, however, does not offer much support for this concern. This is mainly because it is essentially a post-analysis framework, i.e., the analysis for MFS comes after the completion of test case generation and execution. As a result, in the generation stage, testers have no knowledge of the possible MFS, and surely it is possible that multiple MFS appear in the same test case.

C. Masking effects

When considering a single execution of the test set, traditional covering array usually offer inadequate testing due to *Masking effects* [4], [5]. A masking effect [5] is an effect that some failures or exceptions prevent a test case from testing all valid schemas in that test case, which the test case is normally expected to test. For example in Table IV, t_1 is initially expected to cover six 2-degree schemas, i.e., (0, 0, -, -), (0, -, 0, -), (0, -, -, 0), (-, 0, 0, -), (-, 0, -, 0), and (-, -, 0, 0), respectively. The failure of this test case, however, may prevent the checking of these schemas. This is because, the failing of t_1 (*Scroll Type* is set to be *sensitive*) crashed HSQLDB, and as a result, it did not go on executing the remaining test code, which may affect the examination of some interactions of t_1. Hence, we cannot ensure we have thoroughly exercised all the interactions in this failing test case.

Since traditional covering array alone cannot reach adequate testing, as an alternative, *tested t-way interaction criterion* as a more rigorous coverage standard is proposed [5]. According to this criterion, a t-degree schema is covered iff (1) it appears in a passing test case, or (2) it is identified as MFS or faulty schema. Apparently, this criterion can not be satisfied with traditional covering array alone (in practice, it is often the case that the test set is rerun until all test cases pass). Next let us examine whether this criterion can be satisfied with SCT, i.e., the combination of traditional covering array and MFS identification.

One obvious insight is that if there is only **single** MFS in each failing test case, this criterion is satisfied. This conclusion is based on the fact that the MFS identification is actually a process to isolate the failure-inducing interaction among other interactions in the failing test case, and since there is only a single MFS, then other schemas can be determined as non-MFS.

For example in Table IV, t_1 contained a single MFS (-, 0, -, -), and we identified this MFS by generating four extra test cases (t_{10} to t_{13}). As for t_1, the schema (-, 0, -, -) is determined to be MFS, but since the target of that testing is 2-way coverage, i.e., to cover all the 2-degree schemas, this 1-degree schema does not contribute any more coverage. Based on the fact that (-, 0, -, -) is MFS, all the test cases containing this schema will fail by definition, and surely the super-schemas of (-, 0, -, -) in this test case – (0, 0, -, -), (-, 0, 0, -) and (-, 0, -, 0) are also faulty schemas as all the test cases containing these schemas must contain the MFS (-, 0, -, -), which will fail after execution. The remaining 2-degree schemas (0, -, 0, -), (0, -, -, 0), (-, -, 0, 0) are contained in the additionally generated test case t_{11} (0, 1, 0, 0) (Note that for single MFS, there will be at least one passing additionally generated test case), which are of course non-faulty schemas. In the end, all the 2-degree schemas in the failing test case t_1 satisfied the *tested t-way interaction criterion*.

When a failing test case has **multiple** MFS, however, SCT fails to meet that criterion. As discussed previously, SCT cannot properly work on test cases with multiple MFS–and even cannot obtain a valid schema. With this in mind, we cannot determine which schemas in this failing test case are MFS or not. Consequently, we cannot ensure we have examined all the t-degree schemas in this failing test case. For example, t_4 has two MFS–(-, 0, -, -), (-, -, 0, 1), which can not be identified with the OFOT approach (In fact, there is no passing additionally generated test case). As a result, there are two 2-degree schemas (1, 0, -, -) (-, -, 0, 1) in this test case that are neither contained in a passing test case nor determined as MFS or faulty schemas. Hence, *tested t-way interaction criterion* is not satisfied. Since multiple MFS in a test case can introduce masking effects, SCT must be negatively affected as it lacks mechanisms to avoid the appearance of multiple MFS in failing test cases.

Note that in this running example of this paper, *masking effects* are actually caused by the *multiple MFS problem* we discussed previously. However, these two problems focus on different aspects of combinatorial testing. The *masking effects* mainly focus on the test sufficiency of CT, which can be regarded as a metric to evaluate how many schemas are actually tested [5]. While for *multiple MFS problem*, it mainly focuses on the quality of MFS identification. To be convenient, we separately discuss these two problems later in this paper.

D. Augmentation of the SCT

Considering the fact that we do not need to repeatedly identify the same MFS, we can reduce the number of test cases by checking the already identified MFS and removing it from the MFS identification process. For example in Table IV, we do not need to generate 4 additional test cases (t_{18} to t_{21}) to figure out the failure-cause of t_7 is indeed (-, 0, -, -), which has already been identified in previous iteration (t_{10} to t_{13}). Therefore, we only need to check whether there is any MFS other than (-, 0, -, -) in t_7 or not. When applying this augmentation, the overall SCT process of the example in Table IV will evolve into the process shown in Table V.

In Table V, the only difference from Table IV is that for test case $t4$ and t_7, we first checked whether there is any MFS other than the already identified MFS (-, 0, -, -). Hence we generated two additional test cases t_{14} and t_{19} (highlighted), which exclude the MFS (-, 0, -, -) from the original failing test cases $t4$ and t_7. Note that t_{14} (1, 1, 0, 1) was generated by mutating the value of the second parameter of test case t_4 (1, 0, 0, 1) from 0 to 1(but it also can be any value different from the original value 0 of the second parameter in the test case t_4), and as a result, it removed the previously identified MFS (-, 0, -, -). The same as t_{14}, t_{19} (2, 1, 1, 1) was also generated by mutating the value of the second parameter of test case t_7 (2, 0, 1, 1) from 0 to 1. We then found that t_{14} still failed after execution, which indicates that t_{14} contains other different MFS. So, we continued to use OFOT to identify the MFS of t_{14} and obtained the second MFS (-, -, 0, 1). With respect to t_{19}, we found it passed after execution, and hence there is no other MFS in this test case, and we do not need to generate additional test cases. As a result, we have reduced the number of test cases by 2 in total by using the augmented SCT.

Although the augmented SCT can reduce the redundancy of test cases to some extent, there still remain some issues, e.g., multiple MFS, and masking effects, that it cannot deal with.

IV. Interleaving Approach

Considering these deficiencies of SCT, we do not need to cover all t-wise interactions before moving to the debugging phase. As an alternative, it is better to make test case generation and MFS identification more closely cooperate with each other. Hence, we propose a new CT generation-identification framework – ***Interleaving CT*** (ICT). Our new framework aims at enhancing the interaction of generation and identification to reduce the unnecessary and invalid

TABLE V

AUGMENTED SEQUENTIAL CT PROCESS

Generation (Execution)

	test case				Outcome
	o_1	o_2	o_3	o_4	
t_1	0	**0**	0	0	Fail
t_2	0	1	1	1	Pass
t_3	0	2	1	0	Pass
t_4	1	**0**	**0**	**1**	Fail
t_5	1	1	0	0	Pass
t_6	1	2	1	1	Pass
t_7	2	**0**	1	1	Fail
t_8	2	1	0	0	Pass
t_9	2	2	0	0	Pass

Identification

t_1 (0,0,0,0)	t_{10}*	1	0	0	0	Fail
	t_{11}*	0	1	0	0	Pass
	t_{12}*	0	0	1	0	Fail
	t_{13}*	0	0	0	1	Fail
	MFS	**(-, 0, -, -)**				
t_4 (1,0,0,1)	t_{14}*	1	1	0	1	Fail
	t_{15}*	2	1	0	1	Fail
	t_{16}*	1	2	0	1	Fail
	t_{17}*	1	1	1	1	Pass
	t_{18}*	1	1	0	0	Pass
	MFS	**(-, -, 0, 1)**				
t_7 (2,0,1,1)	t_{19}*	2	1	1	1	Pass

test cases discussed previously. In other words, the ultimate goal of this framework is to better support MFS identification and test case generation, so that both of them can alleviate the three problems we discussed in Section III.

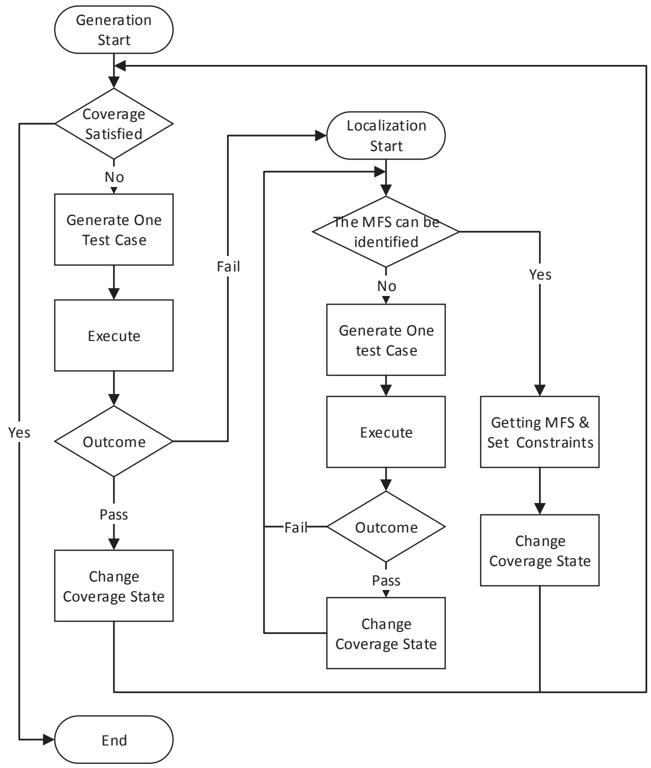


Fig. 2. The Interleaving Framework

A. Overall framework

The basic outline of our framework is illustrated in Figure 2. Specifically, this new framework works as follows: First, it checks whether all the needed schemas are covered or not. Normally the target of CT is to cover all the t-degree schemas, with t assigned as 2 or 3. If the current coverage is not satisfied, it will generate a new test case to cover as many uncovered schemas as possible. After that, it will execute this test case with the outcome of a pass (executed normally, i.e., does not trigger an exception, violate the expected Oracle or the like) or a fail (on the contrary). When the test case passes, we will update the coverage state, as all the schemas in the passing test case are regarded as error-irrelevant. As a result, the schemas that were not covered before will be determined to be covered if it is contained in this newly generated test case. Otherwise, if the test case fails, then we will start the MFS identification module to identify the MFS in this failing test case. One point to note is that if the test case fails, we will not directly change the coverage, as we can not figure out which schemas are responsible for this failure among all the schemas in this test case until we identify them.

The identification module works in a similar way as traditional independent MFS identification process, i.e., repeats generating and executing additional test cases until it can get enough information to diagnose the MFS in the original failing test case. The difference from traditional MFS identifying process is that we record the coverage that this module has contributed to the overall coverage. In detail, when the additional test case passes, we will label the schemas in these test cases as covered if it has not been covered before. When the MFS is found at the end of this module, we will first set them as forbidden schemas that later generated test cases should not contain (Otherwise, the test case must fail and it cannot contribute to more coverage), and second, all the t-degree schemas that are *related* to these MFS as covered. Here the *related* schemas indicate the following three types of t-degree schemas:

First, the MFS **themselves**. Note that we do not change the coverage state after the generated test case fails (both for the generation and identification module), so these MFS will never be covered as they always appear in these failing test cases.

Second, the schemas that are the **super-schemas** of these MFS. By definition of the super-schemas (Definition 3), if the test case contains the super-schemas, it must also contain all its sub-schemas. So every test case that contains the super-schemas of the MFS must fail after execution. As a result, they will never be covered as we do not change the coverage state for failing test cases.

Third, those **implicitly forbidden** schemas, which was first introduced in [24]. This type of schemas is caused by the conjunction of multiple MFS. For example, for a SUT with three parameters, and each parameter has two values, i.e., SUT(2, 2, 2). If there are two MFS for this SUT, which are (1, -, 1) and (0, 1, -). Then the schema (-, 1, 1) is the implicitly forbidden schema. This is because, for any test case that contains this schema, it must contain either (1, -, 1) or (0, 1, -). As a result, (-, 1, 1) will never be covered as all the test cases containing this schema will fail and so we will not change the coverage state. In fact, by Definition 4, they can be deemed as faulty schemas.

The terminating condition of most CT frameworks is to cover all the t-degree schemas. Then since the three types of schemas will never be covered in our new CT framework, we can set them as covered after the execution of the identification module so that the overall process can stop.

Note that in practice, it may be more effective and efficient if we make more use of the debugging information and bug fixing. That is before we go on generating test cases, we should first analyse the MFS that we have already identified and fixed them. After that, we need to re-test the SUT by augmenting the test suites. By doing so, we can further reduce test cases in real software testing scenario.

B. Modifications of CT activities

More details of the modifications of CT activities are listed as follows:

(1) *Modified CT Generation*: We adopt the *one test case one time* method as the basic skeleton of the generation process. Originally, the generation of one test case can be formulated as EQ1.

$$t \leftarrow select(\mathcal{T}_{all}, \Omega, \xi) \tag{EQ1}$$

There are three factors that determine the selection of test case t. $\mathcal{T}_{all}$ represents all the valid test cases that can be selected to execute. Usually, the test cases that have been tested will not be included as they have no more contribution to the coverage. Ω indicates the set of schemas that have not been covered yet. ξ is a random factor. Most CT generation approaches prefer to select a test case that can cover as many uncovered schemas as possible. This greedy selection process does not guarantee an optimal solution, i.e., the final size of the set of test cases is not guaranteed to be minimal. The random factor ξ is used to help to escape from the local optimum (We will not discuss the specific usage of factor ξ in this paper, many papers that focus on generating covering array have given the specific implements).

As discussed in Section III, we should make the MFS not appear in the test cases generated afterward, by treating them as the forbidden schemas. In other words, the candidate test cases that can be selected are reduced, because those test cases that contain the already identified MFS should not appear next. Formally, let $\mathcal{T}_{MFS}$ indicates the set of test cases that contain the already identified MFS, then the test case selection is augmented as EQ2.

$$t \leftarrow select(\mathcal{T}_{all} - \mathcal{T}_{MFS}, \Omega, \xi) \tag{EQ2}$$

In this formula, the only difference from EQ1 is that the candidate test cases that can be selected are changed to $\mathcal{T}_{all} - \mathcal{T}_{MFS}$, which excludes $\mathcal{T}_{MFS}$ from candidate test cases.

(2) *Modified identification of MFS*: Traditional MFS identification aims at finding the MFS in a failing test case. As discussed before, test cases in the covering array are not enough to identify the MFS. Hence, additional test cases should be generated and executed. Generally, an additional test case is generated based on the original failing test case, so that the failure-inducing parts can

be determined by comparing the differences between the additional test cases and the original failing test case. Take the OFOT approach as an example. In Table IV, the additional test case t_{11} is constructed by mutating the second parameter value of the original failing test case t_1. Then as t_{11} passed the testing, we can determine that the second parameter value (-, 0, -, -) must be a failure-inducing element. Formally, let $t_{failing}$ be the original failing test case, Δ be the mutation parts, $\mathcal{P}$ be the parameters and their values, then the additional test case generation can be formulated as EQ3.

$$t \leftarrow mutate(\mathcal{P}, t_{failing}, \Delta) \tag{EQ3}$$

EQ3 indicates that the test case t is generated by mutating the part Δ of the original failing test case $t_{failing}$. Note that the mutated values may have many choices, as long as they are within the scope of $\mathcal{P}$ and different from those in $t_{failing}$. For example, for the original failing test case t_1 (0, 0, 0, 0) in Table IV, let Δ be the second parameter value, then test cases (0, 1, 0, 0) and (0, 2, 0, 0) all satisfy EQ3. We refer to all the test cases that satisfy EQ3 as $\mathcal{T}_{candidate}$, which can be formulated as EQ4.

$$\mathcal{T}_{candidate} = \{\ t \mid t \leftarrow mutate(\mathcal{P}, t_{failing}, \Delta)\ \} \tag{EQ4}$$

Traditional MFS identification process just selects one test case from $\mathcal{T}_{candidate}$ randomly. However, to adapt the MFS identification process to the new CT framework, this selection should be refined.

Specifically, there are two points to note. First, the additional test case should not contain the already identified MFS; second, the additional test case is expected to cover as many uncovered schemas as possible. These two goals are similar to CT generation. Hence, we can directly apply the same selection method to additional test case generation, which can be formulated as EQ5. The same as EQ2, EQ5 excludes the test cases that contain the already identified MFS from the candidate test cases ($\mathcal{T}_{candidate} - \mathcal{T}_{MFS}$) and selects the additional test case which covers the greatest number of uncovered schemas (Ω).

$$t \leftarrow select(\mathcal{T}_{candidate} - \mathcal{T}_{MFS}, \Omega, \xi) \tag{EQ5}$$

(3) *Updating uncovered schemas*: After the MFS are identified, some related t-degree schemas, i.e., *MFS themselves*, *super-schemas* and *implicitly forbidden schemas*, should be set as covered to enable the termination of the overall CT process. The algorithm that seeks to handle these three types of schemas is listed in Algorithm 1.

Algorithm 1 Changing coverage after identification of MFS

Input: $\mathcal{S}_{MFS}$ ▷ already identified MFS
Ω ▷ the schemas that are still uncovered
$\mathcal{T}_{all}$ ▷ all the possible valid test cases
$\mathcal{T}_{MFS}$ ▷ all the test cases that contain the MFS
Output: Ω ▷ updated schemas that are still uncovered

1: **for each** $s \in \mathcal{S}_{MFS}$ **do**
2:     **if** s is t-degree schema **then**
3:         $\Omega \leftarrow \Omega \backslash s$
4:     **end if**
5:     **for each** s_p is super-schema of s **do**
6:         **if** s_p is t-degree schema **then**
7:             $\Omega \leftarrow \Omega \backslash s_p$
8:         **end if**
9:     **end for**
10: **end for**
11: **for each** $s \in \Omega$ **do**
12:     **if** $\nexists t \in (\mathcal{T}_{all} - \mathcal{T}_{MFS}), s.t., t.contain(s)$ **then**
13:         $\Omega \leftarrow \Omega \backslash s$
14:     **end if**
15: **end for**

In this algorithm, we firstly check each MFS (line 1) to see if it is a t-degree schema (line 2). We will set those t-degree MFS as covered and remove them from the uncovered schema set Ω (line 3). This is the first type of schemas –*themselves*. For each t-degree super-schema of these MFS, it will also be removed from the uncovered schema set (line 5 - 9), as they are the second type of schemas – *super-schemas*. The last type, i.e., *implicitly forbidden schemas*, is the toughest one. To remove them, we need to search through each potential schema in the uncovered schema set (line 11) and check if it is the implicitly forbidden schema (line 12). The checking process involves solving a satisfiability problem. Specifically, if we can not find a test case from the set $(\mathcal{T}_{all} - \mathcal{T}_{MFS})$ (excluding those that contain MFS), such that it contains the schema under checking, then we can determine the schema is the implicitly forbidden schema, and it needs to be removed from the uncovered schema set (line 13). This is because in this case, the schema under checking can appear only in $\mathcal{T}_{MFS}$, which we will definitely not generate in later iterations. In this paper, an SAT solver will be utilized to do this checking process.

1) MFS identification approach mutated: To forbid identified MFS in the later generated test cases is efficient for CT because it will reduce many unnecessary test cases. On the other hand, our framework has strict requirements in the accuracy of the identified MFS. This is obvious, because if the schema identified is not an MFS, later generated test cases will forbid a non-MFS schema, which will have two impacts: (1) If this non-MFS schema is the sub-schema of some actual MFS, then the corresponding MFS will never appear, and surely we will not detect and identify it. (2) If this non-MFS schema is a sub-schema of some t-degree uncovered schemas, then these schemas will never be covered, and adequate testing will not be reached.

To exactly identify the correct MFS in one failing test case, if possible, however, is not practical due to the cost of testing [6], [14]. This is because, for any test case with n parameter values, there are $2^n - 1$ possible schemas which are the candidate MFS. For example, the possible candidate schemas of failing test case (1, 1, 1) are (1,-, -), (-, 1, -), (-, -, 1), (1, 1, -), (1, -, 1), (-, 1, 1) and (1, 1, 1). According to the definition of MFS, we need to individually determine whether these $2^n - 1$ are faulty schemas or not. In fact, even to determine whether a schema is a faulty schema or not is not easy, as we must figure out whether all the test cases containing this schema will fail or not. So the complexity to correctly obtain a real MFS is surely exponential. As a result, existing MFS identification approaches actually obtain *approximation* solution through a relatively small size of additionally generated test cases [6], [14], [15], [17]–[19], [25].

Based on this insight, to improve the accuracy of the identified MFS, we propose a novel MFS-checking mechanism to assist with MFS identification. It is detailed in Algorithm 2.

In this algorithm, our target is to verify whether the candidate schema $candi$ is MFS or not. The input variable $Repeat$ indicates the checking strength, that is, the number of iterations that schema $candi$ is checked. In each iteration, we will generate a new test case t_{new} which contains this schema $candi$ (line 4) and execute it (line 5). If the newly generated test case fails, which indicates that the probability that the schema $candi$ is MFS increases, we will continue the checking process until the variable $Repeat$ is equal to 0 (line 9, line 2). On the other hand, if the test case passes (line 5), which indicates that the schema $candi$ is not MFS, we will update the uncovered schemas (because the new passing test case will contribute to more coverage),

Algorithm 2 Checking the MFS

Input: $candi$ ▷ MFS that needs to be checked

$Repeat$ ▷ The number of repeating times

Ω ▷ the schemas that are still uncovered

$\mathcal{T}_{MFS}$ ▷ all the valid test cases that contain MFS

$\mathcal{T}_{candi}$ ▷ all the valid test cases that contain candi

Output: $candi\ is\ MFS\ or\ not$

1: $\mathcal{T}_{Executed} \leftarrow \emptyset$
2: **while** $Repeat > 0$ **do**
3: $\quad\mathcal{T}_{possible} \leftarrow (\mathcal{T}_{candi} \backslash \mathcal{T}_{MFS}) \backslash \mathcal{T}_{Executed}$
4: $\quad t_{new} \leftarrow select\_dissimilar(\mathcal{T}_{possible}, \mathcal{T}_{Executed})$
5: $\quad$**if** $execute(t_{new})$ == PASS **then**
6: $\qquad$update(t_{new}, Ω)
7: $\qquad$**return** False
8: $\quad$**end if**
9: $\quad Repeat \leftarrow Repeat - 1$
10: $\quad\mathcal{T}_{Executed}.append(t_{new})$
11: **end while**
12: **return** True

and directly return false (line 7). If we cannot find a test case that contains this schema and passes during our checking process, we will return true (line 12).

Note that the output $true$ of our checking algorithm does not guarantee this schema $candi$ is 100% MFS (for which we need to generate all the possible test cases containing this schema), however, the probability that this schema is MFS increases with the increasing of checking strength, i.e., the value of $Repeat$ variable. However, on the other hand, increasing the value of $Repeat$ also raises our testing cost (we need to generate one more test case if $Repeat$ increases by 1).

With respect to the tradeoff between the quality of MFS identification and testing cost, we need to design an elaborate test set with a small number of test cases, while keeping a high probability to check whether the candidate schema under test is indeed MFS or not. Inspired by the idea of generating dissimilar test cases [26], [27], for each iteration, we let the newly generated test case be as different from previously generated test cases as possible (line 3-4). This heuristic idea is based on the fact that there is a small probability that dissimilar tests contain the same fault [26]. As a result, if the checking schema is not MFS, but the test case which contains it fails because of other failure-inducing schemas, we may easily verify that it is not the MFS by generating another dissimilar test case (There is a high probability that the newly generated test case does not contain the failure-inducing schema in previous test case, and passes after execution).

It is worth noting that the feedback checking mechanism can also be embedded into SCT. Specifically, we can check the MFS obtained from each failing test case by generating additional test cases. Then, similar to ICT, we need to eliminate those MFS that cannot pass the verification and re-locate the MFS in the corresponding failing test case. However, for SCT, there are two facts that can negatively influence the improvement of the feedback checking mechanism. First, the effects of correcting wrongly identified MFS cannot be further propagated. That is, although we can fix the MFS identification result, it cannot be used in the following cases because the test case generation stage has already finished and some other MFS may never be detected. Second, it costs SCT more for embedding the feedback checking mechanism. This is because SCT needs to identify MFS for more failing test cases than ICT as we have discussed before, and for each failing test case, the feedback checking process needs to run at least one time. Our empirical study also exhibits this point. In fact, even without feedback checking mechanism, SCT still needed more test cases in the MFS identification stage than ICT with feedback checking mechanism (see Table X in Section V-B).

2) Constraints handling: In many systems to be tested, constraints or dependencies exist between parameters. These constraints will render certain test cases invalid [28]. To handle these constraints is important, as we should examine the schemas only with valid test cases [5]. There are two types of method for constraints handling: 1) static method, that is, by knowing the constraints in prior, approaches will forbid those invalid schemas to appear in the generated test cases [20], [28]–[31]. 2) dynamic method, that is, it does not initially know which are constraints, but identify them as MFS and forbid them in the following iterations [5]. We adopt the second method for handling constraints. There are two reasons for this choice. First, there are not many constraints in our empirical study such that the dynamic way of identifying them and forbidding them will not affect the efficiency too much. Second, the dynamic process of handling constraints is similar to the way that we identify the MFS, so our framework does not need to be modified a lot for handling constraints.

Specifically, when we execute invalid test cases which cannot be executed or even compiled, we will identify these invalid schemas which trigger this problem. In other words, we will regard the incompatibility exception as one type of failure, and identify the illegal schemas as MFS. After this, we will forbid these illegal schemas and some possible implicitly illegal schemas to appear in the test cases generated later (through the same way for those identified MFS).

In a more detailed view, those forbidden schemas are formulated into clauses, as introduced in [28]. For example, consider the SUT in Table III. Assume that scroll type *forward-only* is incompatible with *in-process* server type, that is, the forbidden schema is (in-process, forward-only, -, -). We can formulate it as clause {!in-process, !forward-only}, which means that *!in-process* & *!forward-only = 1*, where *in-process* and *forward-only* can be 0 or 1 (0 means that this value is not selected, while 1 means this value is selected). This clause limited that only one of them can be set to be 1. By doing so, we can use SAT solver [32] to obtain a solution (that is, a test case that avoids these forbidden schemas). It is noted that, besides these forbidden schemas, there are other conditions a test case must satisfy. For example, in Table III, each option must be assigned with one, and only one, value. More details of this formulated model can be found in [28], [29].

There are two key parts in our constraints handling techniques. The first part is updating uncovered schemas. That is, after one constraint or one MFS is obtained, we will update all the schemas that are still needed to be covered. This part is done by computing the compatibility between the uncovered schemas with those known and discovered constraints [28]. After this, all the possible implicated constraints (Not known prior, nor explicitly discovered), and hence, our algorithm will not be stuck in the unstoppable condition that some schemas cannot be covered. The second part is that, for one test case that is generated by our approach, we will compute the satisfiability of the value under selected for each parameter. Specifically, for one pending value of one specific parameter, we will first use SAT solver to find if there is a solution (one possible test case) that contain this value and not violate any of these constraints or MFS (including implicated ones). If the solver returns true, which means we can find one satisfied test case, then this value can be selected as one candidate value for that parameter. Otherwise, this value will be discarded.

C. Advantages of our framework

In view of the problems listed in Section III, our new framework has the following advantages:

1) ***Redundant test cases are eliminated so that the overall cost is reduced.***

   Two facts of our framework support this improvement: (1) The schemas appearing in the passing test cases generated for MFS identification are counted towards the overall coverage, so that the test case generation process converges faster, which results in generating a smaller number of test cases. (2) The forbidden of identified MFS. As a result, test cases which contain these MFS will not appear, as well as those additionally generated test cases used to re-identify these MFS.

2) ***The appearance of multiple MFS in the same test case is limited, improving the effectiveness of MFS identification.***

   This is mainly because we forbid the appearance of MFS that has been identified. Consequently, following our approach, the number of remaining MFS decreases one by one. Correspondingly, the probability that multiple MFS appear in the same test case will also decrease. Since multiple MFS has a negative effect on MFS identification as discussed in Section III, the reduction of the appearance of multiple MFS in the same test case obviously improves the effectiveness of MFS identification.

3) ***The Masking effect is reduced, and hence, adequate testing is better satisfied.***

   As discussed in Section III, SCT suffers from masking effects when there are multiple MFS in one failing test case. Since our approach theoretically reduces the probability that multiple MFS appear in the same test case, we believe our framework can alleviate the masking effects. In fact, our framework conforms to *tested t-way interaction criterion* because we only update t-way coverage for two types of schemas : (1) t-degree schemas in those passing test cases and (2) t-degree schemas *related* to MFS. Hence, our ***Interleaving CT*** framework supports better adequate testing than SCT.

4) ***The quality of MFS identification is improved even if Assumption 2 is not satisfied.***

   As we have discussed in Section 2.2, the MFS identification approach used in our framework is based on the "Safe Value" Assumption (Assumption 2). In practice, however, this assumption is not always satisfied, which may result in a bad quality of MFS identification result. Under such condition, the feedback checking mechanism process can alleviate this issue and improve the quality of MFS identification. Specifically, with additional test cases generated in the feedback checking mechanism process, we obtain more chances to refine the MFS identification result, i.e., we can re-identify the MFS in the failing test case if the previous result cannot pass our validation. Note that the high quality of the MFS identification result is important to our framework because the test cases generated later by our framework is heavily based on the previously identified MFS.

D. Demonstration on an example

Applying the new framework to the scenario of Section III, we can get the result listed in Table VI.

TABLE VI
INTERLEAVING CT CASE STUDY

Generation					***Identification***				
t_1	0	0	0	0 Fail					
					t_2*	1	0	0	0 Fail
					t_3*	0	1	0	0 Pass
					t_4*	0	0	1	0 Fail
					t_5*	0	0	0	1 Fail
					candidate MFS: $(-, 0, -, -)$				
					Checking				
					t_6*	1	0	1	1 Fail
					t_7*	2	0	2	2 Fail
t_8	1	1	1	1 Pass					
t_9	0	2	1	1 Pass					
t_{10}	0	1	0	1 Fail					
					t_{11}*	1	1	0	1 Fail
					t_{12}*	0	2	0	0 Fail
					t_{13}*	0	1	1	0 Pass
					t_{14}*	0	1	0	0 Pass
					candidate MFS: $(-, -, 0, 1)$				
					Checking				
					t_{15}*	2	1	0	1 Fail
					t_{16}*	1	2	0	1 Fail
t_{17}	1	2	0	0 Pass					
t_{18}	2	1	0	0 Pass					
t_{19}	2	2	1	1 Pass					

This table consists of two main columns, in which the left column indicates the generation part while the right indicates the identification process. We can find that, after identifying the candidate MFS (-, 0, -, -) for t_1, we generated two additional test cases (The checking strength, i.e., the $Repeat$ value, is 2 in this example) that contain this schema and found both of them failed. It means that the schema (-, 0, -, -) passed the verification, and would be regarded as MFS. Note that if either one of these two additional test cases passes, we will label (-, 0, -, -) as non-MFS, and re-identify the MFS in t_1. Another point that needs to be noted is that these two additional test cases (t_6, t_7) are two dissimilar test cases. In fact, all the 2-degree schemas that are covered by these two test cases are different.

After we determine (-, 0, -, -) to be MFS, the following test cases (t_8 to t_{19}) will not contain this schema. Correspondingly, all the 2-degree schemas that are related to this schema, e.g., (0, 0, -, -), (-, 0, 1, -), will also not appear in the following test cases. Additionally, the passing test case t_3 generated in the identification process cover six 2-degree schemas, i.e., (0, 1, -, -), (0, -, 0, -), (0, -, -, 0), (-, 1, 0, -), (-, 1, -, 0), and (-, -, 0, 0) respectively, so that it is not necessary to generate more test cases to cover them. We later found that t_8 failed, which only contained one MFS as expected, and we easily identified it (-, -, 0, 1) with four extra-generated test cases (t_{11} to t_{14}) and two checking test cases (t_{15} to t_{16}). This schema is 2-degree MFS, which will be forbidden in the following test cases and set to be covered.

Above all, when using the interleaving CT approach, the overall generated test cases are 2 less than that of the traditional sequential CT approach in Table IV and equal to the augmented sequential CT approach in Table V. In fact, if we exclude the test cases from the checking process, the interleaving CT approach can reduce even more test cases (6 less than that of the traditional sequential CT approach, and 4 less than the augmented sequential CT approach). However, these additional test cases generated in the checking process will ensure a high quality of MFS identification for interleaving CT approach. In this simple example, both interleaving CT and augmented sequential CT correctly identified all the MFS (better than that of traditional sequential CT), but given more complex subjects with more MFS, we believe interleaving CT can outperform the augmented sequential CT at MFS identification.

Note that in this example, our approach did not wrongly identify the MFS, and hence, this example did not show how *ict* handles the circumstance if Algorithm 2 returns false (i.e., if one passing test case is found containing the previously identified MFS in the checking process). Next, we use a simple example to show how *ict* works in such condition. Let a SUT have four parameters, of which p_1, p_2, p_3, and p_4 are ternary options. There are two MFS in this SUT, which are (0, 0, 0, -) and (1, 0, 0, -), respectively. Now we assume that *ict* start with a failing test case (0, 0, 0, 0). Table VII shows how *ict* works in this condition.

TABLE VII
EXAMPLE OF HOW INTERLEAVING CT HANDLES THE WRONG IDENTIFICATION CASE

Generation						***Identification***					
t_1	0	0	0	0	Fail						
						t_2*	1	0	0	0	Fail
						t_3*	0	1	0	0	Pass
						t_4*	0	0	1	0	Pass
						t_5*	0	0	0	1	Fail
						candidate MFS: $(-, 0, 0, -)$					
						Checking					
						t_6*	2	0	0	1	Pass
						Re-identify					
						t_7*	2	0	0	0	Pass
						t_8*	0	2	0	0	Pass
						t_9*	0	0	2	0	Pass
						t_{10}*	0	0	0	2	Fail
						candidate MFS: $(0, 0, 0, -)$					
						Checking					
						t_5*	0	0	0	1	Fail
						t_{10}*	0	0	0	2	Fail

In Table VII, we can observe that at the first time, we wrongly identified the MFS. Specifically, after four test cases (t_1, t_2, t_3, and t_4) generated by *ict*, we identified schema (-, 0, 0, -) as the MFS instead of the real MFS (0, 0, 0, -). The reason why it fails obtaining the real MFS is that t_1 introduced the new MFS (1, 0, 0, -). It violated the safe assumption as we discussed in Section II-B (Assumption 2 in the last two paragraphs), and hence, it cannot obtain the real MFS. After this, *ict* needed to check this schema by generating additional test case t_6 (2, 0, 0, 1). It passed during testing, which indicated that we wrongly identified the MFS, i.e., (-, 0, 0, -) is not the real MFS. Then *ict* re-started the MFS identification procedure and generated additional four test cases, i.e., t_7, t_8, t_9, and t_{10}. Note that in the second MFS identification procedure, *ict* needed to generate test cases as different as what has been already generated as possible to cover more un-covered test cases. In the second iteration of the MFS identification, *ict* correctly identified the real MFS (0, 0, 0, -). *ict* then checked this schema by two test cases t_5 and t_{10}. Since these two test cases both failed, (0, 0, 0, -) was identified to be the MFS at last. Note that in the second checking procedure, there did not exist other test cases contain the schema (0, 0, 0, -), and hence, we could only use these two already generated test cases to check this schema. In fact, under this condition, all the possible test cases, i.e., t_1, t_5, and t_{10}, that containing this schema (0, 0, 0, -) were failed. As a result, (0, 0, 0, -) is exactly the MFS according to what MFS is declared (Definition 4).

V. EMPIRICAL STUDIES

To evaluate the effectiveness and efficiency of the interleaving CT approach, we conducted a series of empirical studies on several open-source software subjects. Each of these studies aims at addressing one of the following research questions:

Q1*:* Does *ICT* perform better than augmented *SCT* at the overall cost and the accuracy of MFS identification?

Q2*:* Does *ICT* alleviate the three problems proposed in Section III. Specifically, (1) does ICT reduce generating redundant and useless test cases, (2) does ICT reduce the appearance of test cases which contain multiple MFS, and (3) does ICT reduce the impacts of masking effects?

Q3*:* How much does ICT gain from the feedback checking mechanism.

Q4*:* Does *ICT* have any advantages over the existed masking effects handling technique — *FDA-CIT* [5]?

Q5*:* How well do these approaches perform on software subjects with multiple defects?

Q6*:* What is the sensibility of our approach to a different number of MFS and a different number of options in SUT?

Q7*:* How well does our approach perform when the two assumptions listed in Section II do not hold?

Q8*:* How about the static way, i.e., the Error Locating Arrays, of handling combinatorial test generation and fault localization?

Note that we will refer to SCT as the *augmented SCT* approach in the remaining part of this paper (Augmented SCT performs more effective and efficient than traditional SCT).

A. Subject programs

The five subject programs used in our experiments are listed in Table VIII. Column "Subjects" indicates the specific software. Column "Version" indicates the specific version that is used in the following experiments. Column "LOC" shows the number of source code lines for each software. Column "Faults" presents the fault ID, which is used as the index to fetch the original fault description from the bug tracker for that software. Column "Lan" shows the programming language for each software (For subjects written in more than one programming language, only the main programming language is shown).

TABLE VIII
SUBJECT PROGRAMS

Subjects	Version	LOC	Faults	Lan
Tomcat	7.0.40	296138	#55905	java
Hsqldb	2.0rc8	139425	#981	Java
Gcc	4.7.2	2231564	#55459	c
Jflex	1.4.2	10040	#87	Java
Tcas	v_1	173	#Seed	c

Among these subjects, Tomcat is a web server for java servlet; Hsqldb is a pure-java relational database engine; Gcc is a programming language compiler; Jflex is a lexical analyzer generator; Tcas is a module of an aircraft collision avoidance system. We select these programs as subjects because their behaviours are influenced by various combinations of configuration options or inputs. For example, the component *connector* of Tomcat is influenced by more than 151 attributes [33]. For program Tcas, although with a relatively small size (only 173 lines), it has 12 parameters with their values ranging from 2 to 10. As a result, the overall input space for Tcas can reach 460800 [34], [35].

As the main target of our empirical studies is to compare the ability to handle the proposed three issues between our approach with traditional ones, we firstly must know these faults and their corresponding MFS in prior, so that we can determine whether the schemas identified by those approaches are accurate or not. For this, we looked through the bug tracker of each software and focused on the bugs which were caused by the interaction of configuration options. Then for each such bug, we derived its MFS by analysing the bug description report and the associated test file which can reproduce the bug. For Tcas, as it does not contain any fault for the original source file, we took a mutation version for that file with injected fault. The mutation was the same as that in [35], which is used as an experimental object for the fault detection studies.

1) Specific inputs models: To apply CT on the selected software, we need to firstly model their input parameters. As discussed before, the whole configuration options are extremely large so that we cannot include all of them in our model in consideration of the experimental time and computing resource. Instead, a moderate small set of these configuration options is selected. It includes the options that cause the specific faults in Table VIII so that the test cases generated by CT can detect these faults. Additional options are also included to create some noise for the MFS identification approach. These options are selected randomly. Details of the specific options and their corresponding values of each software are posted at `http://gist.nju.edu.cn/doc/ict/`. A brief overview of the inputs models, as well as the corresponding MFS (degree), is shown in Table IX.

TABLE IX
INPUTS MODEL

Subjects	Inputs	MFS
Tomcat	$2^8 \times 3^1 \times 4^1$	1(1) 2(2)
Hsqldb	$2^9 \times 3^2 \times 4^1$	3(3)
Gcc	$2^9 \times 6^1$	3(4)
Jflex	$2^{10} \times 3^2 \times 4^1$	2(1)
Tcas	$2^7 \times 3^2 \times 4^1 \times 10^2$	9(16) 10(8) 11(16) 12(8)

In this table, Column "inputs" depicts the input model for each version of the software, presented in the abbreviated form $\#values^{\#number\ of\ parameters} \times ...$, e.g., $2^9 \times 3^2 \times 4^1$ indicates the software has 9 parameters that can take on 2 values, 2 parameters taking on 3 values and only one parameter taking on 4 values. Column "MFS" shows the degrees of each MFS and the number of MFS (in the parentheses) with that corresponding degree.

Note that these inputs just indicate the combinations of configuration options. To conduct the experiments, some other files are also needed. For example, besides the XML configuration file, we need a prepared HTML web page and a java program to control the startup of the tomcat to see whether exceptions will be triggered. Other subjects also need some corresponding auxiliary files (e.g., c source files for GCC, SQL commands for Hsqldb, and some text for Jflex). Additionally, there are two constraints among the subjects. The first constraint is from Tomcat, of which the error page location must not be empty. The second one is from Hsqldb, of which someone can only process with the "*next()*" method in a non-scrollable result set.

B. Comparing ICT with SCT

The covering array generating algorithm used by *ICT* is AETG [8], as it is the most common one-test-case-one-time generation algorithm. Another reason for choosing AETG, which is also the most important, is that the mutation of this algorithm, i.e., AETG_SAT [28], [29] is a rather popular approach to handle constraints in covering array generation, which is the key to our framework. The MFS identifying algorithm is OFOT [6] as discussed before. The constraints handling solver (integrated into AETG_SAT) is a java SAT solver – SAT4j [36]. Note that all the three algorithms or techniques can be easily replaced with other similar approaches. For example, we can use other one-test-one-time covering array generation algorithms, like DDA [9], or other MFS identification techniques [17], [18], or other popular SAT solvers [37]. However, to select specific algorithms for the three components of combinatorial testing is not the key concern of this paper; instead, our work focuses on the overall CT process.

With respect to *SCT*, we used the augmented simulated annealing approach [11], [38] to build covering array. The heuristic search-based algorithm is known to produce smaller covering arrays than the one test case at one time approach. Hence, using this approach is fairer for the approach *SCT* than using greedy approach (which may result in a larger size of covering array) because it needs to firstly generate a complete covering array.

1) Study setup: For each software except *Tcas*, a test case was determined to be passing if it ran without any exception; otherwise, it was regarded as failing. For *Tcas*, as the fault is injected, we determined the result of a test case by separately running and comparing the original correct version and the mutated version.

In this experiment, we focused on three coverage criteria, i.e., 2-way, 3-way, and 4-way, respectively. It is known that the generated test cases vary for different runs of AETG algorithm and simulated annealing algorithm. So to avoid the biases of randomness, we conducted each experiment 30 times and then evaluated the results. (Note that the remaining case studies were also based on 30 repeated experiments.) For each run of the experiment, we separately applied SCT approach and our approach to the prepared subject to detect and identify the MFS.

To evaluate the results of the two approaches, one metric is the cost, i.e., the number of test cases that each approach needs. Specifically, the test cases that were generated in the CT generation and MFS identification, respectively, were recorded and compared for these two approaches. Apart from this, another important metric is the quality of their identified MFS. For this, we used standard metrics: *precision* and *recall*, which are defined as follows:

$$precision = \frac{\#the\ num\ of\ correctly\ identified\ MFS}{\#the\ num\ of\ all\ the\ identified\ schemas}$$

and

$$recall = \frac{\#the\ num\ of\ correctly\ identified\ MFS}{\#the\ num\ of\ all\ the\ real\ MFS}$$

Precision shows the degree of accuracy of the identified schemas when compared to the real MFS. *Recall* measures how well the real MFS are detected and identified. Their combination is F-measure, defined as

$$F - measure = \frac{2 \times precision \times recall}{precision + recall}$$

2) Result and discussion: Table X presents the results for the number of test cases. In Column 'Method', *ict* indicates the interleaving CT approach and *sct* indicates the sequential CT approach. The results of three covering criteria, i.e., 2-way, 3-way, and 4-way are shown in three main columns. In each of them, the number of test cases that are generated in *CT generation* activity (Column 'Gen'), in *MFS identification* activity (Column 'Iden'), and the total number of test cases (Column 'Total') are listed.

TABLE X
COMPARISON OF THE NUMBER OF TEST CASES

Subjects	Method	2-way			3-way			4-way		
		Gen	Iden	Total	Gen	Iden	Total	Gen	Iden	Total
Tomcat	ict	8.3	**54.2**	60.7	31.1	**50.3**	79.9	78.9	**53.0**	130.2
	sct	13.8	55.0	68.3	38.9	61.0	99.7	92.8	95.5	187.3
Hsqldb	ict	11.7	37.8	49.4	40.7	**47.7**	88.3	113.0	**53.5**	166.3
	sct	15.6	32.3	47.9	48.4	65.1	113.3	123.0	114.0	236.5
Gcc	ict	14.0	28.0	41.4	41.6	47.5	89.0	94.3	50.4	144.7
	sct	14.6	20.1	34.4	52.9	27.8	80.2	101.9	38.8	140.1
Jflex	ict	14.6	17.0	31.6	48.6	**17.0**	65.6	133.7	**17.0**	150.7
	sct	15.9	16.6	32.5	49.9	24.1	74.0	133.2	44.5	177.7
Tcas	ict	109.1	0.0	109.1	414.7	3.0	417.7	1545.4	7.4	1552.8
	sct	107.5	0.0	107.5	418.3	0.0	418.3	1556.1	2.6	1558.7

One observation from this table is that, in most cases, the number of test cases generated by our approach was smaller than that of the *sct* approach. In fact, except for subject *Gcc*, our

TABLE XI

COMPARISON OF THE QUALITY OF THE IDENTIFIED MFS

Subjects	Method	2-way			3-way			4-way		
		Precision	Recall	F-measure	Precision	Recall	F-measure	Precision	Recall	F-measure
Tomcat	ict	1.0	1.0	**1.0**	1.0	1.0	**1.0**	1.0	1.0	**1.0**
	sct	0.75	1.0	0.86	0.88	1.0	0.93	0.88	1.0	0.93
Hsqldb	ict	1.0	0.77	**0.83**	1.0	1.0	**1.0**	0.97	1.0	**0.99**
	sct	0.7	0.4	0.5	0.53	0.47	0.49	0.45	0.43	0.43
Gcc	ict	0.45	0.28	**0.34**	0.77	0.65	**0.7**	0.83	0.75	**0.79**
	sct	0.13	0.07	0.1	0.09	0.07	0.08	0.12	0.1	0.11
Jflex	ict	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	sct	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Tcas	ict	0.0	0.0	0.0	0.0	0.0	0.0	0.15	0.0	**0.01**
	sct	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

approach reduced about dozens of test cases on average when compared to approach *sct* (The improvement for subject *Tcas* was smaller, because most of the MFS of *Tcas* are of high degree ($t > 6$), and the covering arrays ($t = 2, 3, 4$) rarely detected any of them.). This result indicates that *ict* was more efficient at both *CT generation* activity and *MFS identification* activity.

For *Gcc*, however, we found that *ict* generated a bit more test cases at *MFS identification* activity (Note that even for this subject, *ict* still generated fewer test cases at *CT generation* activity). However, when considering the fact that *ict* obtained a higher quality of the identified MFS, we believe this cost was worth it for *Gcc*. In fact, the f-measures of *ict* were 0.34, 0.7, and 0.78, respectively, for subject *Gcc*, while *sct* only scored 0.1, 0.08, and 0.11, respectively. This gap between *ict* and *sct* for subject *Gcc* was far larger than that of other subjects.

The quality of the identified MFS for other subjects is also listed in Table XI. Based on this table, we found that *ict* performed better than *sct*. In fact, except for subject *Jflex*, of which both *ict* and *sct* perfectly identified the MFS (the MFS of *Jflex* is a single 2-degree schema and easy to identify), *ict* obtained a higher score at *f-measure* than *sct* for all the subjects. For example, the *f-measures* of *ict* were 0.83, 1.0, and 0.99, respectively for subject *Hsqldb*, while *sct* only scored 0.5, 0.49, and 0.43, respectively. Even for subject *Tcas*, at which failures are hard to detect, the f-measure of *ict* was 0.01 for 4-way coverage, while *sct* scored 0. This result indicates that *ict* was far more effective at MFS identification than *sct*.

Another interesting observation with regard to the MFS identification is that higher t-wise strengths were not always resulting in an improved precision (Take subject *Hsqldb* for example, the f-measure of *ict* and *sct* for 3-way coverage were 1.0 and 0.49, respectively; while 0.99 and 0.43 for 4-way coverage). This is because the effectiveness of MFS identification is related to the degree of MFS (i.e., the number of parameter values in the MFS) contained in the SUT. That is, if all the MFS in the SUT is of low degree, a lower strength covering array is enough to detect the MFS. Specifically, a t-wise covering array can detect all the failures caused by the MFS of t-degree, or less than t-degree. Then, if an MFS is detected, *ict* and *sct* can identify them as expected. A higher-wise covering array can certainly detect those low degree MFS too, but compared to the lower strength covering array, it generates much more test cases. As a result, many failing test cases may contain the same MFS, and worse, it increases the chance that a failing test case contains multiple MFS. This surely decreases the accuracy of MFS identification (See Section III-B).

Additionally, Table XII shows the milliseconds consumed by the two approaches on average. The experiment was conducted on Machine HP ProDesk 600 G1 TWR (Intel Core i5, 3.3Hz, 16GB memory). Based on this table, it is obvious that *ict* cost more time than *sct*. This is because *ict* needed to handle the SAT problem (for forbidding the appearance of MFS and constraints), which consumed additional computing resources than *sct*. Considering the long test case execution time of large software projects, however, this extra test case generation time of *ict* is trivial in most cases.

TABLE XII

TIME CONSUMES (MILLISECOND)

Subject	Method	2-way	3-way	4-way
Tomcat	ict	556.4	2703.7	12367.7
	sct	10.0	56.7	305.6
Hsqldb	ict	345.5	2093.6	21918.4
	sct	16.7	151.3	1055.1
Gcc	ict	180.1	1117.5	5408.5
	sct	8.0	68.0	309.3
Jflex	ict	187.1	1747.1	11412.4
	sct	75.5	288.8	2491.4
Tcas	ict	178.0	2914.9	60725.5
	sct	135.6	1750.0	25380.7

In summary, the answer to **Q1** is: **Our approach *ict* needs fewer test cases than the augmented sequential CT approach, and the quality of MFS identification of *ict* is higher than *sct*.**

C. Alleviation of the three problems

Section III shows three problems that impact the performance of CT process, which are *redundant test case generation*, *multiple MFS in the same test case* and *masking effects*, respectively. To learn if *ict* can alleviate these problems, we re-use the experiment in the first study, i.e., let *sct* and *ict* generate test cases to identify the MFS in the five program subjects. Then, we respectively investigate the extent to which ICT and SCT are affected by those issues. It is noted that the original definition [5] of tested-t-way coverage including the t-degree tuples that may appear in the non-option-related failed test case. In our experiments(including the following sections), all these failures are option-related. Hence, the computation of the tested-t-way coverage in our experiments satisfied the original definition.

1) Study setup: We designed three metrics for each of the three problems. First, to measure the *redundant test case generation*, we gathered the number of times that each schema was covered. This metric directly indicates the redundancy of generated test cases, because it is obvious that if there are too many schemas that are repeatedly being covered by different test cases, then the CT process is inefficient (if one schema is covered and tested, it is unnecessary to check them again with other test cases). Note that this metric is closely related to the number of test cases discussed in the previous study, more test cases surely make schemas being covered more times. However, there exists one difference, i.e., test cases can evenly cover many schemas for a relatively few times, or alternatively, some schemas are covered many times, but others not.

Second, to measure *multiple MFS in the same test case*, we directly searched for each generated test case and checked whether it contained more than one MFS or not.

Third, we used the *tested-t-way* coverage criterion [5] to measure the masking effects. Specifically, we re-computed the coverage of the test cases generated by ICT and SCT by counting all the t-degree schemas that were either covered in a passing test case or identified as MFS or faulty schema. For ICT and SCT, the higher is the *tested-t-way* coverage, the more adequate is the testing and hence the less masking effects.

2) Result and discussion: 1) **Redundant test cases**.

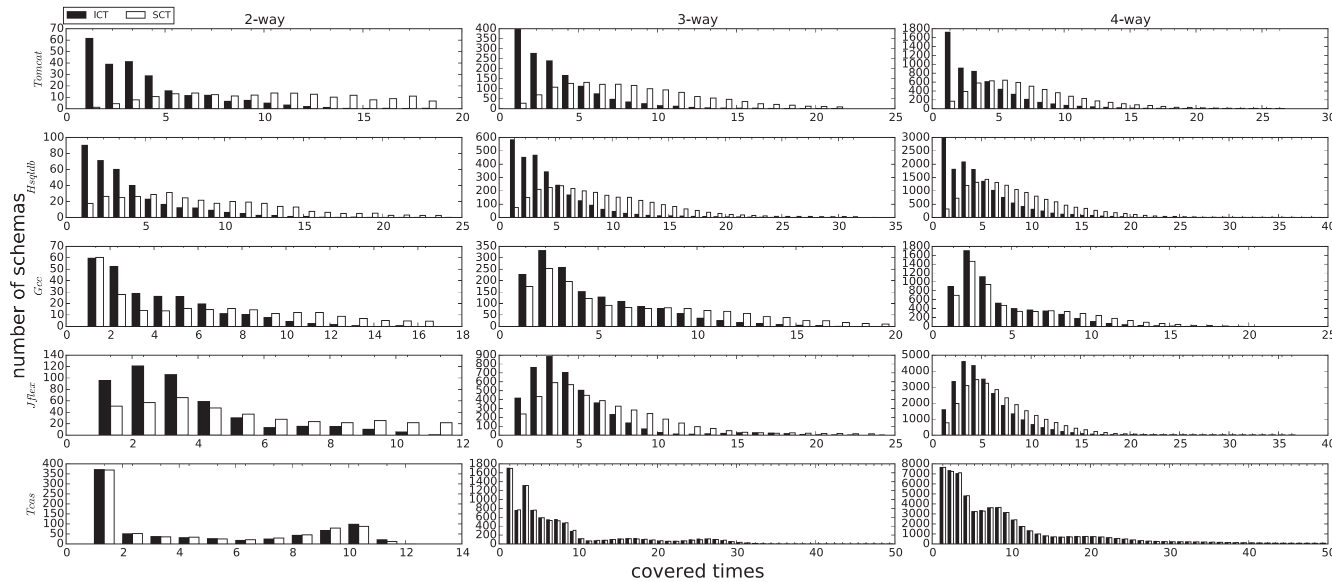


Fig. 3. The redundancy of test cases

Our result is shown in Figure 3. This figure consists of 15 sub-figures, one for each subject with specific testing coverage (ranged from 2 - 4 way). For each sub-figure, the x-axis represents the number of times a schema is covered in total, and the y-axis represents the number of schemas. For example in the first sub-figure (2-way for Tomcat), two bars with x-coordinate equal to 1 indicates that *ict* approach had 61.5 schemas on average which were covered once and *SCT* had 1.3 schemas.

As discussed previously, the more schemas are covered with a low-frequency, the less redundant the generated test cases are. Hence it implies effective testing if the number of schemas (y-axis) decreases with the increase of the covered times (x-axis). With respect to Figure 3, it is easy to find that for most of the 15 sub-figures, *ict* performed better than *sct*. In fact, for *ict*, the bars decreased rapidly with the increase of the‘ x-axis, while for *sct*, the trend was more smooth. See subject tomcat with 2-way coverage, for example, *ict* had about 61.5 schemas which were only covered once, about 38.9 schemas covered twice, less than 12 schemas covered more than 6 times. For *sct*, however, for most covered times, it had about 10 schemas, which indicates a very low performance.

The interesting exception is subject Tcas, on which *ict* and *sct* showed a similar trend. This is because all the MFS of Tcas are of high degree (t > 6), and the covering arrays (t = 2, 3, 4) rarely detected any of them. Under this condition, since both approaches rarely detected the

MFS, the overall process was transferred to be traditional covering array generation (the MFS identification process is omitted).

This result shows that our two modifications of the traditional approach, i.e., taking account of the covered schemas by test cases generated in MFS identification and forbidding the appearance of existing MFS to reduce the test cases that are used to identify the same MFS, are useful, especially when the MFS are detected and identified.

2) **Multiple MFS.**

The result is shown in Table XIII, which lists the number of test cases (on average for the repeated 30 experiments) that contain more than one MFS.

TABLE XIII
NUMBER OF TEST CASES THAT CONTAIN MULTIPLE MFS

Subject	Method	2-way	3-way	4-way
Tomcat	ict	0.0	0.0	0.0
	sct	1.2	4.6	10.8
Hsqldb	ict	0.0	0.0	0.0
	sct	0.2	1.6	4.1
Gcc	ict	0.5	0.8	0.6
	sct	0.2	1.8	3.4
Jflex	ict	0.0	0.0	0.0
	sct	0.0	0.0	0.0
Tcas	ict	0.0	0.0	0.0
	sct	0.0	0.0	0.0

From this table, one observation is that *ict* obtained a better result than *sct* at limiting the test cases which contain multiple MFS. For all the subjects except *Gcc*, *ict* nearly eliminated all the test cases which contain multiple MFS. Even for *Gcc*, the size of test cases which contain multiple MFS was limited in a very small number (smaller than 1). For *sct*, however, the result was not as good as *ict*. In fact, except for subjects *Jflex* and *Tcas*, *sct* suffered from generating test cases which contain multiple MFS. This is one reason why even though *sct* generated many more test cases than *ict*, it did not obtain a better MFS identification result than *ict*. Two exceptions are subjects *Jflex* and *Tcas*, on which both *ict* and *sct* did not generate test cases containing multiple MFS. The reason is that *Jflex* has only one MFS (see Table IX) and the MFS of *Tcas* are all high degrees which are hardly detected.

3) **Masking effects**.

TABLE XIV

MASKING EFFECTS RESULTS

Subjects	Method	Tested-t-way coverage		
		2-way	3-way	4-way
Tomcat	ict	**236.0(100.00%)**	**1424.0(100.00%)**	**5600.0(100.00%)**
	sct	233.8(99.07%)	1397.2(98.12%)	5501.7(98.24%)
Hsqldb	ict	**357.0(100.00%)**	**2742.0(100.00%)**	**14135.5(100.00%)**
	sct	352.1(98.63%)	2713.7(98.97%)	13984.5(98.93%)
Gcc	ict	**251.4(99.76%)**	**1526.4(99.38%)**	**5997.6(99.17%)**
	sct	250.0(99.21%)	1519.4(98.92%)	5908.2(97.69%)
Jflex	ict	**473.0(100.00%)**	**4282.0(100.00%)**	**26532.0(100.00%)**
	sct	468.8(99.11%)	4216.6(98.47%)	26177.5(98.66%)
Tcas	ict	837.0(100.00%)	9158.0(100.00%)	64696.0(100.00%)
	sct	837.0(100.00%)	9158.0(100.00%)	64696.0(100.00%)

The results of masking effect for each approach is shown in Table XIV. Specifically, the number of t-degree (t = 2, 3, 4) schemas which are *tested* (in the passing test cases or identified as faulty schemas) are gathered, as well as the percentage of the total t-degree schemas (in the parentheses followed). Several observations can be obtained from this result:

First, the extent to which *sct* and *ict* suffered from masking effects is not severe. Actually, the lowest tested-t-way coverage of *ict* is 99.17% (4-way for Gcc), and *sct* is 97.69% (4-way for Gcc). This result shows that combining MFS identification with covering array (either in a sequential way or interleaving way) can make testing more adequate than using covering array alone.

Second, *ict* was more effective than *sct* at handling the masking effects. With respect to *tested-t-way* coverage, *ict* covered almost all the tested-t-way schemas for all the subjects (except for *Gcc*, but for which *ict* still covered more tested-t-way schemas than *sct*). On the other hand, *sct* was not as good as *ict*. In fact, *sct* fell behind *ict* for almost all the subjects except *Tcas*. For subject *Tcas*, both *ict* and *sct* covered all the tested-t-way schemas (failures of *Tcas* were rarely detected, and all the t-degree schemas appeared in the passing test cases).

In summary, the answer to **Q2** is that **our approach *ict* can alleviate the three problems discussed in Section III, and when compared to *sct*, *ict* is a better approach to resolve these issues. Additionally, both *ict* and *sct* have a good performance in reducing the masking effects.**

D. The benefits of feedback checking mechanism

One important part of the *ict* approach is the feedback checking mechanism, which aims at judging whether the schemas identified by *ict* is real MFS or not by additionally generating test cases containing the schemas under check. It is interesting to evaluate how valuable is this feedback checking mechanism, i.e., how much improvement *ict* gained from this mechanism.

1) Study setup: For this, we created a mutation version of *ict* by removing the feedback checking mechanism from the original *ict* approach. We later call this mutation approach the *ict-nonfb*. Then, we applied this approach to test the five subjects listed in Table VIII and identified the MFS contained in them. At last, we evaluated the benefits of the feedback checking mechanism by comparing the results obtained by *ict-nonfb* and *ict*.

2) Result and discussion: We list the results of the number of test cases generated by *ict-nonfb* in Table XV, the f-measure of MFS identification in Table XVI, the average number of test cases containing multiple MFS in Table XVII, and the tested-t-way coverage in Table XVIII. Additionally, we attached the gaps between *ict-nonfb* with ict in the parentheses. The value with a negative sign indicates the reduction in the corresponding metric (e.g., number of test cases, the f-measure, the number of test cases containing multiple MFS, the tested-t-way coverage) made by *ict-nonfb* when compared with *ict*, while non-negative sign indicates the increase in that corresponding metric.

TABLE XV
NUMBER OF TEST CASES GENERATED BY *ict* WITHOUT FEEDBACK CHECKING

Subject	2-way	3-way	4-way
Tomcat	42.8(-17.9)	65.0(-14.9)	115.2(-15.0)
Hsqldb	41.0(-8.4)	74.2(-14.1)	147.4(-18.9)
Gcc	37.0(-4.4)	75.0(-14.0)	121.4(-23.3)
Jflex	29.2(-2.4)	63.2(-2.4)	148.8(-1.9)
Tcas	111.0(**1.9**)	414.6(-3.1)	1548.0(-4.8)

The following could be observed:

1) *ict-nonfb* generated a smaller amount of test cases than *ict*. Specifically, except for the *tcas* program subject, *ict-nonfb* reduced the number of test cases by about 1.9 to 23.3. This is as expected because the feedback checking mechanism needs to generate additional test cases to check whether the schemas identified by *ict* is real MFS or not.

TABLE XVI

THE F-MEASURE OBTAINED BY *ict* WITHOUT FEEDBACK CHECKING

Subject	2-way	3-way	4-way
Tomcat	1.0(0.00%)	1.0(0.00%)	1.0(0.00%)
Hsqldb	0.74(-9.00%)	0.64(-36.00%)	0.64(-34.57%)
Gcc	0.45(**10.95%**)	0.46(-24.29%)	0.23(-55.71%)
Jflex	1.0(0.00%)	1.0(0.00%)	1.0(0.00%)
Tcas	0.0(0.00%)	0.0(0.00%)	0.01(0.00%)

TABLE XVII

NUMBER OF TEST CASES CONTAIN MULTIPLE MFS FOR *ict* WITHOUT FEEDBACK CHECKING

Subject	2-way	3-way	4-way
Tomcat	0.0(0.0)	0.0(0.0)	0.0(0.0)
Hsqldb	0.0(0.0)	0.0(0.0)	0.0(0.0)
Gcc	0.4(-0.1)	0.2(-0.6)	1.2(**0.6**)
Jflex	0.0(0.0)	0.0(0.0)	0.0(0.0)
Tcas	0.0(0.0)	0.0(0.0)	0.0(0.0)

2) The quality of the MFS identification of *ict-nonfb* decreased a lot. In fact, except for the 2-way coverage of *Gcc*, *ict* either obtained higher f-measures or performed equally well on all the remaining subjects of all the t-ways (2, 3, and 4-way coverage). Additionally, the gaps between them ranged from 9% to 55.7%, which is not trivial.

3) There were no distinct gaps between *ict-nonfb* and *ict* at the number of test cases that containing multiple MFS. In fact, for all the subjects except for *Gcc*, *ict-nonfb* and *ict* both generated 0 test case that containing multiple MFS. For *Gcc*, *ict-nonfb* performed better at 2-way (but the gap is only 0.1) and 3-way coverage, while *ict* performed better at 4-way coverage.

4) The tested-t-way coverage of *ict-nonfb* also decreased. In fact, besides those subjects that *ict-nonfb* and *ict* performed equally well, *ict-nonfb* reduced the tested-t-way coverage by about 0.02% (0.2 tested-2-way schemas) to 4.94% (296.4 tested-4-way schemas).

To summarize, the answer to **Q3** is that: **Without feedback checking mechanism, the number of test cases generated by *ict* reduced, but the quality of MFS identification and tested-t-way coverage decreased significantly. It indicates that the additional test cases generated in feedback checking mechanism is worthwhile, and it is beneficial to**

TABLE XVIII

THE TESTED-T-WAY COVERAGE OBTAINED BY *ict* WITHOUT FEEDBACK CHECKING

Subject	2-way	3-way	4-way
Tomcat	236.0(0.00%)	1424.0(0.00%)	5600.0(0.00%)
Hsqldb	356.8(-0.06%)	2729.4(-0.46%)	14026.8(-0.77%)
Gcc	251.2(-0.08%)	1485.6(-2.67%)	5701.2(-4.94%)
Jflex	473.0(0.00%)	4282.0(0.00%)	26532.0(0.00%)
Tcas	837.0(0.00%)	9158.0(0.00%)	64696.0(0.00%)

adopt feedback checking mechanism in the CT process (in order to obtain a better MFS identification result and a higher tested-t-way coverage).

E. Comparison with FDA-CIT

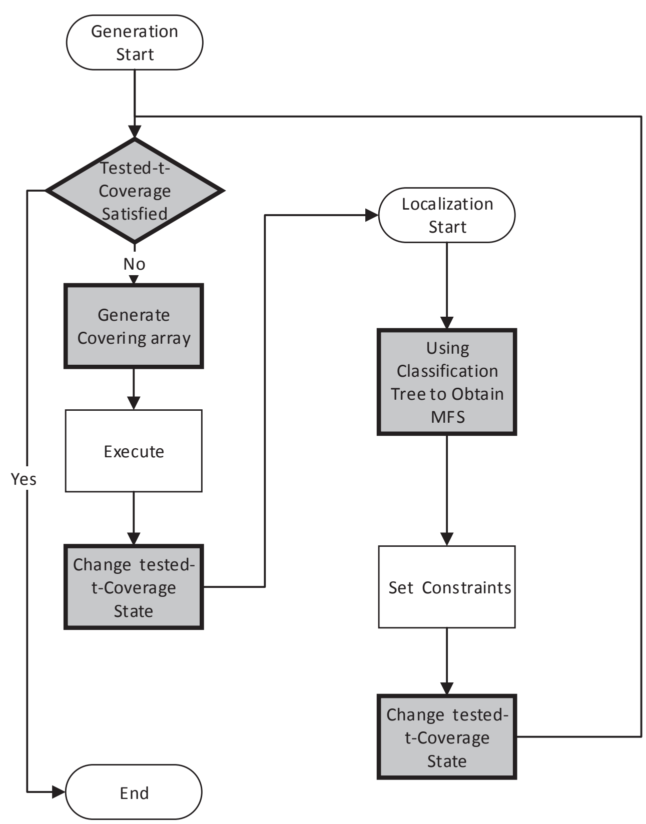


Fig. 4. The Framework of fda-cit

fda-cit [5] is a feedback framework that can augment the traditional covering array to iteratively identify the MFS and can handle the masking effects. The overall process can be illustrated in

Figure 4. Specifically, it will first generate a t-way covering array and execute all the test cases in it. After that, it will utilize the classification tree method to identify the MFS. Then it will forbid the identified MFS to appear and compute the tested-t-way coverage. If the tested-t-way coverage is not satisfied, it will repeat the previous process, i.e., generating additional test cases and identifying MFS. Like our *ict* approach, FDA-CIT is also an adaptive approach which iteratively generates test cases and identifies the MFS. Besides these commonalities, there are several important differences between our approach and *fda-cit* (shaded in Figure 4):

First, the **granularity** of adaptation. Instead of handling one test case one time as *ict*, *fda-cit* tries to generate a batch of test cases at each iteration (A complete covering array will be generated at the first iteration, and more test cases will be supplemented to cover those t-degree schemas which are masked at the following iterations). To generate a batch of test cases may improve the degree of parallelism of testing, but this coarser granularity may also introduce some problems, e.g., some test cases generated at one iteration may fail with the same MFS, which is a potential waste because it is better to use one failing test case to reveal one particular MFS.

Second, the **MFS identification** approach is different. *fda-cit* uses the classification tree on existing executed test cases to characterize the MFS. Different from our OFOT approach, this post-analysis technique does not need additional test cases, but as a side effect, it cannot precisely find the MFS. Worse, the effectiveness of this post-analysis approach depends greatly on the covering array, e.g., if there are a large number of failing tests, and a small size test suite, there is little information to exclude the particular MFS [18].

Third, the **coverage criterion** is not the same. *fda-cit* directly uses the tested-t-way coverage to guide their process. This supports better adequate testing and reduces the impacts of masking effects. As we will see later in our experiments, however, the incorrect MFS identification may prevent *fda-cit* from reaching this type of coverage.

1) Study setup: The design of this case study is similar to the previous two. For each subject in Table VIII, we applied *fda-cit* to generate test cases and identify the MFS. After that, we gathered the overall test cases generated (*fda-cit* does not need additional test cases to identify the MFS), MFS identification results(including recall, precision, and f-measure), and the other three metrics, i.e., covered times of schemas, the number test cases which contain multiple MFS, and the tested-t-coverage. The same as previous experiments, we repeated each experiment 30 times for different coverage (2, 3, and 4 way), and then gathered and analysed the average data. Note that the MFS identification approach in the *fda-cit* has two versions, i.e., ternary-class and multiple-class. In this paper, we use the multiple-class version for comparison, as it performs better than the former [5]. Another point needs to be noted is that we also used the augmented simulated annealing approach [11], [38] to build covering array for the *FDA-CIT*.

2) Result and discussion: 1) **Total number of test cases.** The total number of test cases generated by *fda-cit* for each subject is shown in Table XIX. To better evaluate the performance of *fda-cit*, we list the gaps between FDA-CIT with ict and sct respectively in the parentheses (the first number is for *ict*, the second one is *sct*). The value with a negative sign indicates the reduction in the test cases between *fda-cit* and other two approaches, while the value without negative sign indicates the number of test cases which *fda-cit* generated more than the other two approaches.

TABLE XIX
NUMBER OF TEST CASES GENERATED BY *fda-cit*

	2-way	3-way	4-way
Tomcat	28.4(-32.3,-39.9)	65.5(-14.4,-34.2)	147.4(**17.2**,-39.9)
Hsqldb	29.9(-19.5,-18.0)	83.5(-4.8,-29.8)	201.2(**34.9**,-35.3)
Gcc	21.7(-19.7,-12.7)	63.4(-25.6,-16.8)	120.7(-24.0,-19.4)
Jflex	19.8(-11.8,-12.7)	64.5(-1.1,-9.5)	179.5(**28.8**,**1.8**)
Tcas	109.9(**0.8**,**2.4**)	416.6(-1.1,-1.7)	1544.7(-8.1,-14.0)

From this table, one observation is that *fda-cit* was better than *sct* in almost all cases. Combining the results of previous studies for *sct* and *ict*, we can conclude that *sct* was the most inefficient approach at test case generation. Second, for *ict* and *fda-cit*, there were ups and downs on both sides. In detail, *fda-cit* needed fewer test cases at lower coverage (2-way and 3-way coverage), while *ict* performed better at higher coverage (4-way).

This result is reasonable. First, *fda-cit* did not need additional test cases to identify the MFS, which would reduce some cost when compared with *ict*, especially when the coverage is low (For low coverage, the test cases generated by *ict* in the MFS identification stage account for a considerable proportion of the overall test cases). On the other hand, as noted earlier, the coarse-grained generation would make fda-cit generate some unnecessary test cases.

2) **F-measure of MFS identification.** The results of the quality of MFS identification by *fda-cit* is listed in Table XX. Same as the previous metric, the comparison between fda-cit with *ict* and *sct* is also attached (the first number is for *ict*, the second one is *sct*).

TABLE XX
THE F-MEASURE OF MFS IDENTIFICATION FOR *fda-cit*

	2-way	3-way	4-way
Tomcat	0.22(-77.57%,-63.28%)	0.31(-69.09%,-61.94%)	0.33(-66.67%,-59.52%)
Hsqldb	0.32(-51.26%,-18.26%)	0.29(-71.12%,-20.45%)	0.32(-66.19%,-10.76%)
Gcc	0.07(-26.48%,-2.19%)	0.4(-30.28%,**31.50%**)	0.49(-29.57%,**38.29%**)
Jflex	1.0(0.00%,0.00%)	1.0(0.00%,0.00%)	1.0(0.00%,0.00%)
Tcas	0.0(0.00%,0.00%)	0.0(0.00%,0.00%)	0.0(-0.81%,0.00%)

This table shows a discernible disparity between *fda-cit* with the other two approaches. In fact, besides subject *Jflex* of which all three approaches accurately identified the single low-degree MFS (with F-measure equal to 1), and subject *Tcas* of which all three approaches could hardly detect failures (with F-measure equal to 0), *ict* led over *fda-cit* by about 26% to 77%, which is not trivial. The result is similar when comparing *sct* with *fda-cit*.

This result suggests that the classification tree approach used by *fda-cit*, although very resource-saving (does not need additional test cases), is ineffective to accurately identify MFS, especially when there are multiple MFS with high degrees.

Note that *fda-cit*'s primary concern is to avoid masking effects and to give every t-degree schema a fair chance to be tested, not to perform fault characterization. On the other hand for the classification tree method, when only a very small set of test cases fail, it will result in the input data for classification tree to be highly unbalanced [39]. Another point is that all the MFS identified by the classification tree method should contain the same parameter value on the root, which will result in the schemas identified by *fda-cit* tending to be super-schema of the real MFS.

3) **Redundant test cases.** The result is listed in Figure 5. The same as Figure 3, for each sub-figure, the x-axis represents the number of times a schema is covered in total, and the y-axis represents the number of schemas. To enable an intuitive comparison with *ict* and *sct*, we attach the data for *ict* and *ict*, with the solid line and dotted line, respectively.

From this figure, we can see the trend of the bars of *fda-cit* matches pretty well with the curve representing *ict*, which has a significant advantage over the curve of *sct*. This result implies that the test case redundancy of *ict* is similar to that of *fda-cit*, which is not severe when compared with *sct*.

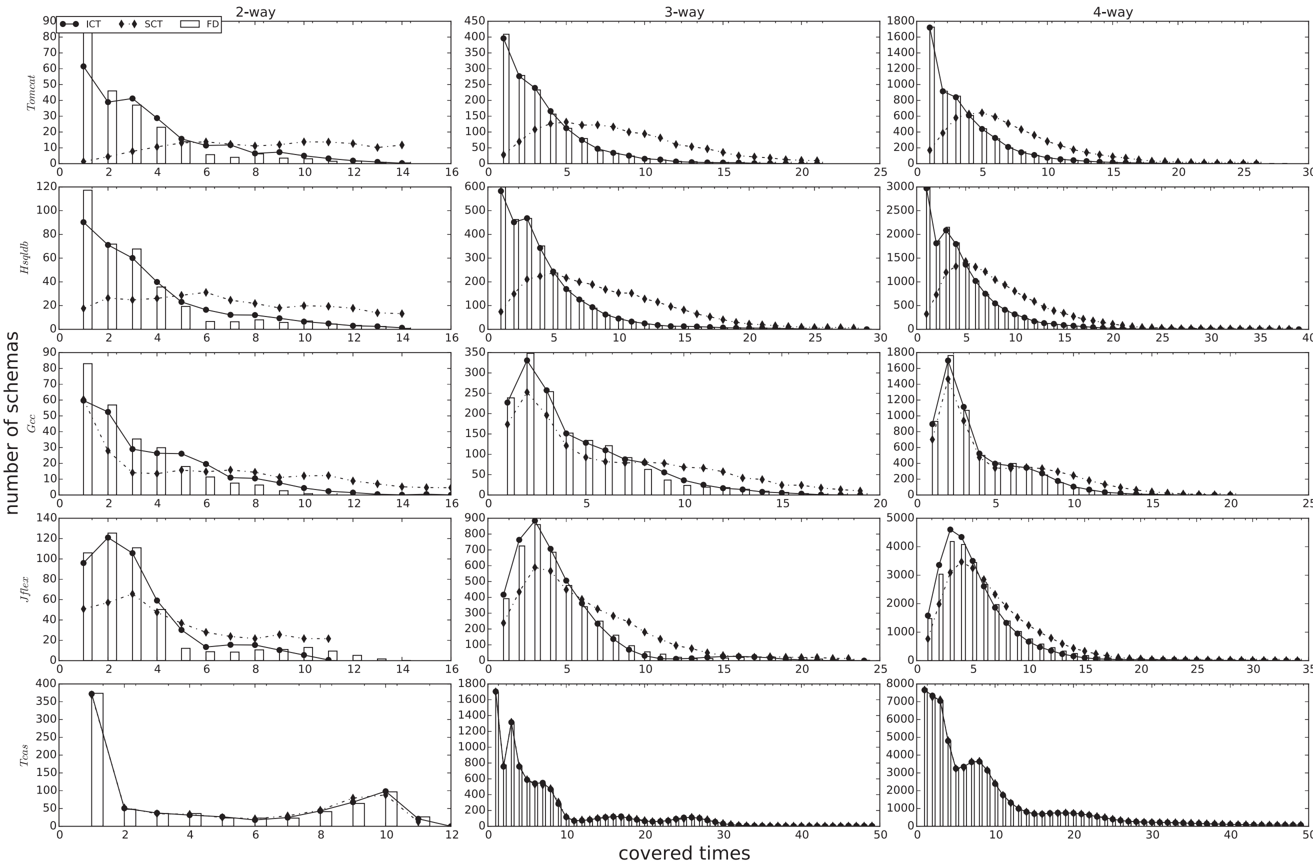


Fig. 5. The redundancy of test cases generated by *fda-cit*

4)**Test cases containing multiple MFS.** Table XXI shows the number of test cases that contain multiple MFS on average for *fda-cit*. The same as before, we also list the gaps between *fda-cit* with *ict* and *sct* respectively in the parentheses (the first number is for *ict*, the second one is for *sct*). From this table, we can easily find that *fda-cit* did almost the same as *sct* at restricting the appearance of test cases that contain multiple MFS. However, both of them did not as well as *ict*. In fact, except for subject *Jflex* (which contains single MFS) and *Tcas* (which contains high-degree MFS that are rarely detected), *fda-cit* generated more test cases that contain multiple MFS than *ict*, and the gap between them increased with the increase of test coverage (*fda-cit* generated about 1 more test cases for 2-way coverage, 2 more test cases for 3-way coverage, and 5 more test cases for 4-way coverage). This result shows that *ict* was the best approach among them to reduce the appearance of test cases that contain multiple MFS, and we also believe this is one reason why *ict* obtained a higher-quality of MFS identification.

5)**Masking effects**. The result is listed in Table XXII, which shows the results of *tested-t-way*

TABLE XXI

NUMBER OF TEST CASES CONTAIN MULTIPLE MFS FOR *fda-cit*

	2-way	3-way	4-way
Tomcat	0.9(**0.9**,-0.3)	4.5(**4.5**,-0.1)	9.8(**9.8**,-1.0)
Hsqldb	0.4(**0.4**,**0.2**)	1.5(**1.5**,-0.1)	4.9(**4.9**,**0.8**)
Gcc	2.4(**1.9**,**2.2**)	2.5(**1.7**,**0.7**)	4.1(**3.5**,**0.7**)
Jflex	0.0(0.0,0.0)	0.0(0.0,0.0)	0.0(0.0,0.0)
Tcas	0.0(0.0,0.0)	0.0(0.0,0.0)	0.0(0.0,0.0)

coverage. The gaps between *fda-cit* with *ict* and *sct* are listed in the parentheses, respectively (the first one is *ict*, the second one is *sct*).

With regard to *tested-t-way* coverage, we can find that our approach *ict* was still the best approach at reducing the masking effects, even though when compared with approach *fda-cit*. In fact, among the 15 cases listed in Table XXII, there are 13 cases on which *ict* performed equal to or better than *fda-cit* (The only two exceptions are *Gcc* for 3-way and 4-way coverage). Note that in some particular cases, the gaps between *ict* and *fda-cit* are not trivial, e.g., *ict* obtained 10 more percent of tested-t-way coverage than *fda-cit* at 2-way coverage for subject *Tomcat*).

Above all, this result suggests that our approach *ict* does reach the same or better level when compared with *fda-cit* at reducing the masking effects. The conclusion also implies that to limit the masking effects, only using an adaptive framework to separately identify the MFS is not enough; making MFS identification accurate is more important.

TABLE XXII

THE TESTED-T-WAY COVERAGE FOR *fda-cit*

	2-way	3-way	4-way
Tomcat	212.1(-10.13%,-9.28%)	1390.2(-2.37%,-0.50%)	5378.0(-3.96%,-2.25%)
Hsqldb	345.1(-3.33%,-1.99%)	2725.1(-0.62%,0.42%)	14096.7(-0.27%,0.80%)
Gcc	250.2(-0.48%, 0.08%)	1530.8(0.29%,0.74%)	6017.5(0.33%,1.82%)
Jflex	473.0(0.00%,0.89%)	4282.0(0.00%,1.53%)	26532.0(0.00%,1.34%)
Tcas	837.0(0.00%,0.00%)	9158.0(0.00%,0.00%)	64695.9(-0.00%,-0.00%)

To summarize, the answer to **Q4** is that **when compared to the adaptive CT approach *fda-cit*, *ict* did better at MFS identification, reduction of masking effects, and reduction of**

test cases containing multiple MFS in most cases, while *fda-cit* generated a smaller number of test cases.

Note that one reason that *ict* did not generate more test cases than *fda-cit* is that all the subjects we used in the experiments have just one test file for each test configuration. Here test configuration equals to the test case we discussed throughout the paper. *fda-cit* is designed to work better for subjects of which one configuration has multiple test files. Under the scenario of multiple test files, *ict* should separately handle each of them, because each test file may contain distinct MFS. As a result, the number of additional configurations needed will grow linearly with the number of failing test files. In this case, *fda-cit* needs a smaller amount of test cases [5].

F. Multiple defects

Since there is only one defect in each software subject used in the previous experiments, it is interesting to observe how well these approaches work on programs with multiple defects. To identify the MFS in the programs with multiple defects is more complex than in the software with a single defect. One problem is that one defect may crash the system under test so that other defects will not have the chance to be triggered. Even worse, some defects may have interference with each other [40], e.g., constructive and destructive interference [41], making fault localization more difficult. For all these reasons, it is important to conduct experiments on multiple defects.

1) Study setup: The software subjects with multiple bugs used in this experiment are listed in Table XXIII. In this table, we listed corresponding versions of each software, lines of code, number of classes, the bug IDs, their corresponding input model, and MFS information.

Note that in this study we only selected 2 out of 5 subject applications to experiment with multiple defects. The reason for this is that it is very hard and time-consuming to obtain reproducible testing scenarios that contain multiple option-related defects. In order to simplify the process, we adopted the strategy to select a small number of subject application, but for each subject application, we obtained more different versions of that application. By doing so, we can also reuse the test scripts we have built for a subject application. As a result, for the experiments of multiple defects, we have built five different versions of subject applications, of which the number is equal to the number of the subject applications used in the experiment for a single defect. This is also why we only use a limited number of bugs for these applications. Also, we believe it is common that the test cases under execution have limited number of multiple bugs. This is because in practice if there are too many distinct defects is the SUT, it needs human re-examination rather than just doing an automatic diagnosis [18].

TABLE XXIII
THE SOFTWARE SUBJECTS WITH MULTIPLE DEFECTS

Software	Version	Loc	Classes	Bug #	Input Model	MFS
Hsqldb	2.0rc8	139425	495	#981 & #1005	$2^9 \times 3^2 \times 4^1$	3(5)
	2.2.5	156066	508	#1173 & #1179	$2^8 \times 3^3$	2(1) 1(1)
	2.2.9	162784	525	#1286 & #1280	$2^8 \times 3^3$	3(2) 2(1) 1(1)
Jflex	1.4.1	10040	58	#87 & #80	$2^{10} \times 3^2 \times 4^1$	1(2)
	1.4.2	10745	61	#98 & #93	$2^{11} \times 3^2 \times 4^1$	2(1) 1(1)

For each version of the subjects, we applied the previous three approaches, i.e., *ict*, *sct*, and *fda-cit*, on generating test cases and fault diagnosis. It is noted that, for *sct* and *ict*, we need to distinguish different faults for them. In our experiments, we simply took the one-bug-at-a-time strategy [40]. More specifically, when identifying the MFS for one particular defect, we only labeled the test cases failed with this specific defect as *fail*, and labeled other test cases (either passed after execution or failed with other defects) as *pass*.

2) Result and discussion: We list the results of the number of test cases generated in this experiment in Table XXIV, the f-measure of MFS identification in Table XXV, the average number of test cases containing multiple MFS in Table XXVI, and the tested-t-way coverage in Table XXVII.

There are several observations in the experiments with multiple defects:

1) The results of the number of test cases satisfied the following relationship: *fda-cit* generated the smallest number of test cases in most cases, and the second-best was *ict*, while the last one was *sct*. Specifically, *fda-cit* reduced the number of test cases by 20.36 on average at 2-way coverage when compared with the approach *sct*, and 19.2 at 3-way coverage, and 65.7 at 4-way coverage. *fda-cit* also reduced the number of test cases by about 20.6 when compared with *ict* at 2-way coverage, but generated slightly more test cases than *ict* at 3-way coverage and 4-way coverage (increased of 2.7 and 0.6, respectively). With respect to *ict*, it reduced the number of test cases by about 21.9 and 66.4 at 3-way and 4-way coverage, respectively, when compared with *sct*. These two approaches generated almost the same number of test cases at 2-way coverage.

TABLE XXIV

NUMBER OF GENERATED TEST CASES (MULTIPLE DEFECTS)

Software	Approach	2-way	3-way	4-way
hsqldb 2.0rc	ict	37.2	129.8	216.2
	sct	41.2	111.6	212.2
	fda-cit	21.0	196.2	170.2
hsqldb 2.25	ict	40.4	56.0	101.2
	sct	42.0	87.8	171.2
	fda-cit	22.8	50.6	115.2
hsqldb 2.29	ict	48.2	77.6	122.6
	sct	40.0	88.4	186.2
	fda-cit	39.4	51.2	115.4
Jflex 1.4.1	ict	45.4	71.4	131.8
	sct	61.2	120.8	247.6
	fda-cit	22.8	61.2	163.4
Jflex 1.4.2	ict	68.0	72.4	145.6
	sct	53.6	108.4	232.0
	fda-cit	30.2	61.8	156.4

2) With respect to the quality of MFS identification, these three approaches satisfied the following relationship: *ict* obtained the highest score at MFS identification, followed by *sct* and *fda-cit*. In fact, except for the 2-way coverage at which *ict* and *sct* obtained almost the same f-measure on average, *ict* increased the f-measure at least by 30% and 32% on average, respectively, at 3-way and 4-way coverage when compared with other two approaches.

3) The results that related to the number of test cases containing multiple MFS satisfied the following relationship: *ict* generated the smallest number of test cases that containing multiple MFS in most cases, and the second-best approach was *fda-cit*, while the last one was *sct*. Specifically, *ict* reduced the number of test cases containing multiple MFS by about 1.0 at the 2-way coverage when compared with *fda-cit*, 3.84 at the 3-way coverage, and 10.04 at the 4-way coverage. For *fda-cit*, it reduced the number of test cases by about 0.2 at the 3-way coverage when compared with *sct*, and 2.52 at the 4-way coverage (These two approaches generated a similar number of test cases that containing multiple schemas at 2-way coverage).

4) Concerning the tested-t-way coverage, these three approaches satisfied the following relationship: *sct* covered the most number of tested-t-way schemas, followed by approaches *fda-cit*

TABLE XXV

THE F-MEASURE OF THE MFS IDENTIFICATION (MULTIPLE DEFECTS)

Software	Approach	2-way	3-way	4-way
hsqldb 2.0rc	ict	0.11	0.96	0.78
	sct	0.33	0.34	0.25
	fda-cit	0.04	0.25	0.15
hsqldb 2.25	ict	0.93	1.0	1.0
	sct	0.86	0.72	0.56
	fda-cit	0.23	0.04	0.0
hsqldb 2.29	ict	0.52	0.81	0.84
	sct	0.4	0.57	0.53
	fda-cit	0.17	0.17	0.19
Jflex 1.4.1	ict	1.0	1.0	1.0
	sct	0.88	0.92	0.96
	fda-cit	0.1	0.0	0.0
Jflex 1.4.2	ict	0.76	1.0	1.0
	sct	0.96	0.72	0.72
	fda-cit	0.16	0.0	0.0

and *ict*, respectively. In fact, except for the 2-way coverage at which *sct* and *ict* covered almost the same number of tested-t-way schemas, *sct* outperformed the other two approaches at 3-way and 4-way coverage. Specifically, *sct* increased the tested-3-way coverage by 20% and 16%, when compared with approaches *ict* and *fda-cit*, respectively, and increased the tested-4-way coverage by 38% and 16%, respectively.

The reason why *ict* was clearly outperformed by *sct* at reducing masking effects under multiple defects (this is the only different conclusion when compared with the results of Section V-E) is that the decreasing of the tested-t-way coverage of *ict* was caused by the reduction of passing test cases. This is because due to the one-bug-at-one-time strategy for handling multiple defects, *ict* labeled the test cases which failed with the defects other than the defect under analysis as passing test cases. As a consequence, it can normally identify the MFS for the defect, but these test cases which failed with other defects cannot contribute to any tested-t-way coverage. Therefore, the tested-t-way coverage obtained by *ict* decreased.

Above all, the answer to Q5 is:

Except for the masking effects, other results matched well with the results obtained from

TABLE XXVI
THE NUMBER OF TEST CASES CONTAINING MULTIPLE MFS (MULTIPLE DEFECTS)

Software	Approach	2-way	3-way	4-way
hsqldb 2.0rc	ict	0.0	0.6	0.4
	sct	0.6	1.4	6.4
	fda-cit	0.4	2.6	4.0
hsqldb 2.25	ict	0.8	0.8	0.4
	sct	0.6	2.2	7.0
	fda-cit	0.6	3.2	7.6
hsqldb 2.29	ict	1.4	1.8	2.2
	sct	1.4	5.8	17.6
	fda-cit	5.0	9.0	16.4
Jflex 1.4.1	ict	1.0	1.0	1.0
	sct	4.6	12.4	26.2
	fda-cit	2.2	6.6	17.4
Jflex 1.4.2	ict	1.0	1.0	0.2
	sct	0.6	3.6	9.8
	fda-cit	1.0	3.0	9.0

the experiments of a single defect. Specifically, *ict* obtained the best MFS identification results and generated the least number of test cases containing multiple MFS, *sct* obtained the most tested-t-way coverage, and *fda-cit* generated the smallest number of test cases.

G. Sensitivity of the approaches

In order to reduce the bias of the choice of subjects, and to obtain a more general conclusion, we conducted several experiments on the subjects with various characteristics in this section. More specifically, we considered the impacts of different numbers of MFS in the SUT and different numbers of options in the SUT on three approaches, i.e., *ict*, *sct*, and *fda-cit*.

1) Study setup: To vary parameters of interest in a controlled setting in this study, we used synthetic subjects instead of real programs (the real program typically represents only one particular parameter setting, and hence it is hard to get software with the expected number of options or MFS).

Specifically, for the first study, that is, evaluating the performance of approaches under different numbers of MFS, we used the subject with 11 parameters, and each parameter had 5 values, i.e., the inputs model is (5^{11}). Then we considered the following possible numbers of 2-degree

TABLE XXVII
THE TESTED-T-WAY COVERAGE (MULTIPLE DEFECTS)

Software	Approach	2-way	3-way	4-way
hsqldb 2.0rc	ict	92.8(25.99%)	956.0(34.87%)	3211.8(22.72%)
	sct	142.2(39.83%)	1214.2(44.28%)	5732.6(40.55%)
	fda-cit	122.8(34.40%)	1123.4(40.97%)	4845.8(34.28%)
hsqldb 2.25	ict	194.8(68.83%)	862.4(45.03%)	3004.0(34.90%)
	sct	190.8(67.42%)	1299.6(67.86%)	5383.4(62.54%)
	fda-cit	181.0(63.96%)	1031.6(53.87%)	4115.2(47.81%)
hsqldb 2.29	ict	177.2(62.61%)	815.6(42.59%)	2716.0(31.55%)
	sct	207.4(73.29%)	1301.6(67.97%)	5624.4(65.34%)
	fda-cit	162.4(57.39%)	1129.4(58.98%)	5141.8(59.73%)
Jflex 1.4.1	ict	273.0(66.10%)	1644.0(47.57%)	7680.0(39.14%)
	sct	328.6(79.56%)	2588.0(74.88%)	14154.0(72.14%)
	fda-cit	281.4(68.14%)	2232.8(64.61%)	12652.0(64.49%)
Jflex 1.4.2	ict	336.6(71.16%)	1896.0(44.28%)	8438.0(31.80%)
	sct	319.8(67.61%)	2955.6(69.02%)	17741.4(66.87%)
	fda-cit	269.2(56.91%)	2241.8(52.35%)	14309.2(53.93%)

MFS: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20, 30, 40, 50, 60, 70, 80 and 90. The detailed information of each synthetic subject application is shown in Table 31 in Appendix B. Then for each run of the experiment, we first injected the corresponding number of MFS into the synthetic subject and then ran all the three approaches on the subject. At last, the results of each approach were collected and analysed.

The second study is to evaluate the performance of approaches under various numbers of options. Hence we used synthetic subjects with the following numbers of options (8, 9, 10, 12, 16, 20, 30, 40, 50, 60, 70, 80, 90, 100). The detailed information of each synthetic subject application is shown in Table 32 in Appendix B. Each option had two values, and each subject had three 2-degree MFS. Then for each subject, we applied the three approaches and compared their performance.

2) Number of MFS: The results for the sensitivity of the number of MFS are shown in Figure 6, 7 and 8, of which the first figure focuses on the quality of MFS identification, the second figure shows the cost, and the last one shows the results of the masking effects.

One observation from Figure 6 is that, with the increasing of the number of MFS, the f-

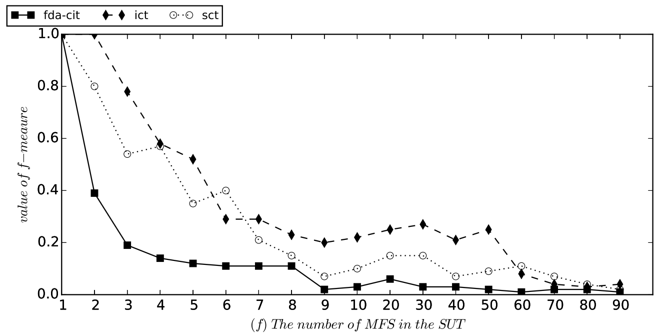


Fig. 6. F-measure for various numbers of MFS

measures of all three approaches decreased rapidly. In fact, when the number of MFS was greater than 60, the f-measures of all three approaches were near 0. This is mainly because if there were too many MFS, it was hard to get a passing test case, and hence, it was challenging to distinguish MFS from those schemas which were not related to the failures.

Another observation is that for most cases, *ict* performed the best, then followed by *sct*, and the last was *fda-cit*. It is clear that *ict* can work well under the condition of multiple MFS when compared with the other two approaches.

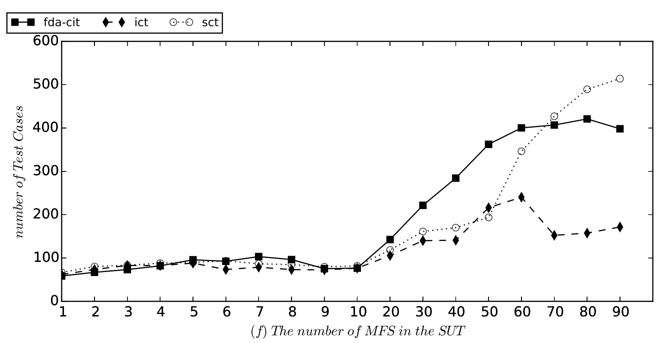


Fig. 7. Test Cases for various numbers of MFS

With regard to the cost, one observation is that with the increasing of the number of MFS, all three approaches needed more test cases to identify the MFS. The reason is also obvious – a high number of MFS can trigger more failing test cases, and in this situation, approaches needed more additional test cases for MFS identification. For *fda-cit*, even though it did not need additional test cases for MFS identification, a high number of MFS would lead to slower convergence. This is because it is harder to fulfill the *tested-t-way* coverage if there are too many failing test cases, and the slower convergence will surely result in generating more test cases.

Another observation about the cost is that *ict* generated the smallest size of test cases when compared to the other two approaches. In fact, when the number of MFS was greater than 20, the cost of *sct* and *fda-cit* increased rapidly (reached to about 500 test cases), which far exceeded that of *ict*.

Regarding the masking effects, one observation is that, with the increase in the number of MFS, the tested-t-way coverage of all these three approaches decreased. This is because, with the increase in the number of MFS, the number of passing test cases decreased, i.e., test cases are more likely to fail with these MFS. Worse, since the MFS quality also decreased with the increase in the number of MFS, these approaches can hardly find any schema that satisfies the tested-t-way coverage criteria. Another observation is that when the number of MFS is relatively high, *fda-cit* obtained a slightly higher score at the value of tested-t-way coverage when compared to the other two approaches. We believe it is because that the test cases generated by *fda-cit* contain more passing test cases. Approaches *sct* and *ict*, on the contrary, generated more failing test cases (in the MFS identification stage, *sct* and *ict* generate test cases that are similar to the original failing test case with only one value mutation. As a consequence, these test cases are more likely to fail, especially at the condition of there are many MFS in the SUT).

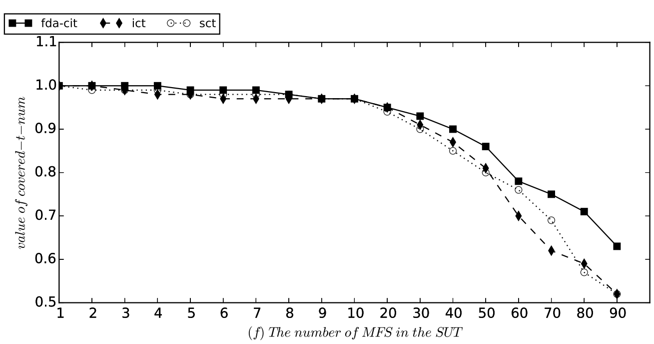


Fig. 8. The tested-t-way coverage for various numbers of MFS

Considering that approaches *ict* and *sct* need to identify the MFS in each of the failing test cases which may contain single MFS or multiple MFS, it is very interesting to observe the performance for these two approaches on the test cases that containing multiple MFS only. Hence, we filtered the results obtained from those failing test cases that only contain single

MFS, and focused on those test cases that contain multiple MFS. The MFS identification results (multiple MFS) are listed in Figure 9. Additionally, we attached the decrease of f-measure of these two approaches when compared with the results on the test cases that are not distinguished by containing single MFS and multiple MFS in Figure 10. Note that there is no data at 1 on the x-axis because there is no test case containing multiple MFS in this condition (the SUT only contains one MFS).

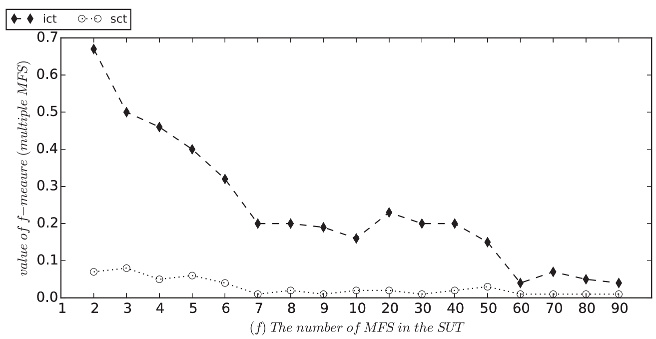


Fig. 9. F-measure (multiple MFS in one test case) for various numbers of MFS

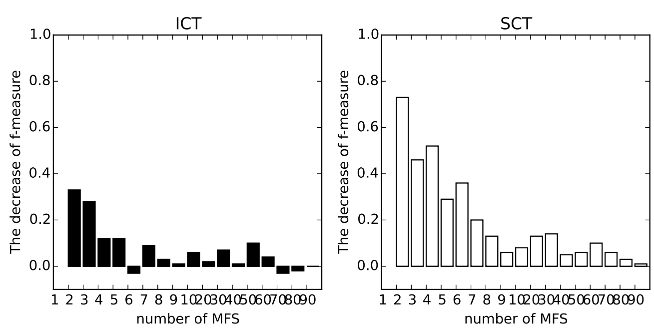


Fig. 10. The decrease of F-measure (multiple MFS in one test case) for various numbers of MFS

We can first observe that approach *ict* outperformed *sct* on MFS identification on test cases that containing multiple MFS. In fact, for all the cases listed in Figure 9, *ict* obtained higher scores of f-measure than *sct* (note that for all the cases, the f-measure of *sct* is under 0.1). The gaps between them ranged from 0.05 to 0.69, which was not trivial. Second, the condition that multiple MFS appear in one test case has significant negative effects on *sct*, while only has a relatively slight influence on *ict*. Specifically, the decrease of f-measure of *sct* (when compared with the f-measure obtained by *sct* on test cases that are not distinguished by single MFS and multiple MFS) ranged from 0.01 to 0.73, while the decrease of f-measure of *ict* was no more than 0.32. In fact, there are three cases (x-axis of 6, 80, and 90) on which *ict* even performed better than before.

Above all, with the increasing of the number of MFS in the SUT, the performance of all three approaches decreased, but *ict* still performed better than the other two approaches.

3) Number of options: The results for the sensitivity of the number of options are shown in Fig. 11, Fig. 12 and Fig. 13, which depicts the quality of MFS identification, the number of generated test cases, and the results of masking effects, respectively.

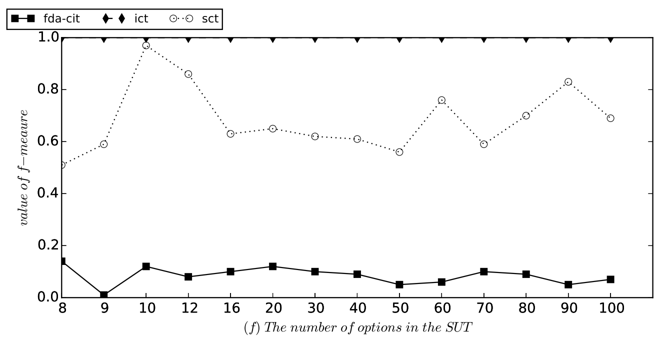


Fig. 11. F-measure for various numbers of options

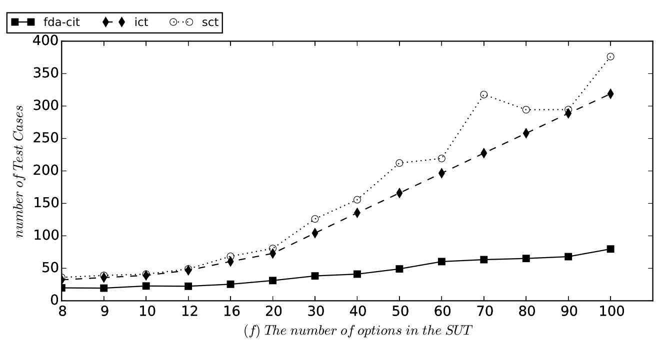


Fig. 12. Test Cases for various numbers of options

With regard to the quality of MFS identification, it is clear that *ict* performed the best, then followed by *sct*, and the last was *fda-cit*. In fact, for all the subjects, *ict* scored 1.0 of f-measure, which indicates that *ict* accurately identified all the MFS. On the other hand, *sct* scored around 0.5 to 0.9, and *fda-cit* only scored around 0.1. This result is consistent with the previous study, indicating that *ict* can accurately identify the MFS, even though when the number of options is

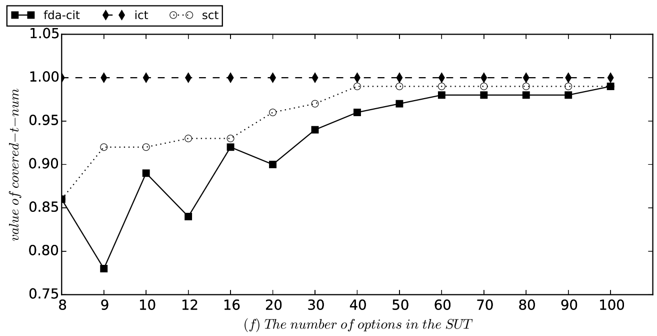


Fig. 13. The tested-t-way coverage for various numbers of options

large. One reason for this result is that the number of test cases generated by *sct* and *fda-cit* that initially had multiple MFS ranged from 2.5 to 6.9 on average, while the number of test cases generated by *ict* which contained multiple MFS was nearly 0.

Another observation about the MFS identification is that there was no clear correlation between the MFS quality and the number of options. In fact, there were no clear regularities for the curves representing the f-measures of *sct* and *fda-cit* with the increasing of the number of options. It shows that the number of options in the SUT did not have much influence on the quality of MFS identification.

With regard to the number of test cases, there was a clear trend that *fda-cit* performed the best, of which the number of needed test cases grew slowly. This is mainly because it did not generate additional test cases for MFS identification. The second best was *ict*, as the number of test cases increased linearly with the number of options in the SUT. This is due to the mechanism of the MFS identification approach applied in the *ict* framework, i.e., we must always generate the same number of test cases as the number of options in the SUT to identify the MFS. Note that if we use the MFS identification algorithms proposed in [17], [18], [25], the number of test cases generated will be reduced. The number of test cases generated by the MFS identification algorithm (OFOT) used in our approach is N, where N is the number of parameter options of the SUT. Hence, the complexity of the MFS identification algorithm (OFOT) used in our approach is (O(N)), while the complexities of others are (O(log N)). In our paper, we did not use other algorithms proposed in [17], [18], [25]. Hence, it is possible that the number of test cases generated in this paper would be further reduced. The last one was *sct*, of which the number of test cases was always larger than that of *ict*.

In regard to the masking effects, we can observe that the number of options had no influence on the results of *ict*. Specifically, *ict* always covered all the tested-t-way schemas no matter what was the number of the options. For the other two approaches, i.e., *sct* and *fda-cit*, their tested-t-way coverage increased with the increase in the number of options. This is because with the increase in the number of options, the number of all the schemas that need to be covered increased, but the number of MFS did not change. As a result, although these two approaches cannot identify the MFS as accurately as *ict*, the proportion of the number of MFS deceased. Hence, the tested-t-way coverage of these two approaches increased.

Therefore, the number of options in the SUT did not have much influence on the quality of MFS identification; and although generating more test cases than *fda-cit*, *ict* was still a better choice when considering the quality of MFS identification and the reduction of masking effects.

In summary, the answer to Q6 is: **Large number of MFS has a negative impact on the quality of the MFS identification of all the three approaches, while the number of options does not. Additionally, concerning various numbers of MFS, *ict* obtained the best MFS identification results and generated the smallest number of test cases in most cases, *fda-cit* obtained the highest covered-t-coverage. As for various numbers of options, *ict* still did the best at MFS identification, and it also obtained the highest covered-t-coverage, while *fda-cit* generated the smallest number of test cases. Besides, in these two conditions, the results obtained by *sct* always lay in between those of the other two approaches.**

H. The ability of handling assumptions

The last study is designed to evaluate the performances of the three approaches when the two assumptions proposed in Section II-B, i.e., deterministic failures and the existence of safe values, do not hold.

1) Study setup: The same as the previous study, in order to make the characteristics of the SUT under control, we decided to use synthetic subjects instead of real programs in this case study. Particularly, synthetic subjects can be injected with various types of faults, e.g., the non-deterministic failures with various probabilities that can be triggered during testing, such that it helps us to evaluate the performance of these approaches for various extents to which these two assumptions do not hold. As a result, we can obtain a more general conclusion instead of those results based on some specific programs.

Specifically, for the first assumption, we decided to inject the MFS that is non-deterministic (the test case which contains it may fail or may not after execution). Then we considered the following possible probabilities that the non-deterministic MFS may be triggered (The probability that the test case which contains it fails after execution): 0.01, 0.05, 0.1, 0.15, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.80, 0.9, and 0.98, respectively. The detailed information of each synthetic subject application is shown in Table 33 in Appendix B. We repeated the experiment 30 times for each probability to avoid the random effects. For each run of the experiment, we applied all the three approaches on the subject and recorded their results (MFS identification quality and cost).

The second study is to evaluate the performance of approaches when the safe value assumption does not hold. In fact, in our previous studies, the safe value assumption was also not always hold. For example, in the first study, we did not give any safe value to our approach *ict*. Instead, we just generated additional test cases containing the schemas under test. As a result, we did not always reach the 100% f-measure of MFS identification. For this study, we decided to evaluate these approaches on the condition that there is no safe value, i.e., every parameter value is contained in at least one MFS. We used synthetic subjects with the input model, and the information of MFS are listed in Table XXVIII. The same as Table IX, input model is presented in the abbreviated form $\#values^{\#number\ of\ parameters} \times ...$, and Column "MFS" shows the degrees of each MFS and the number of MFS (in the parentheses) with that corresponding degree. The detailed information of each synthetic subject application is shown in Table 34 in Appendix B. Then we applied the three approaches on each subject and compared their performance under the condition that there is non-safe value in each subject.

2) Non-deterministic failures: The results of evaluating how well these approaches handle non-deterministic failures are shown in Fig. 14, Fig. 12, and Fig. 16, of which the first figure depicts the quality of MFS identification with various probabilities that the non-deterministic failures are triggered, the second figure shows the number of test cases, and the last one shows the results of the masking effects.

With regard to MFS identification, there are two observations. First, if the probability was below 0.5, all the three approaches did not identify any MFS at all (with f-measure of 0). We believe there are two possible reasons for the low f-measure of all the three approaches. The first one is that if the probability of triggering MFS was too small (below 0.2), approaches could hardly detect the failure, and hence could not identify the MFS. Another one is that if the probability of triggering MFS is around 0.5, then the failure may appear at one testing, but

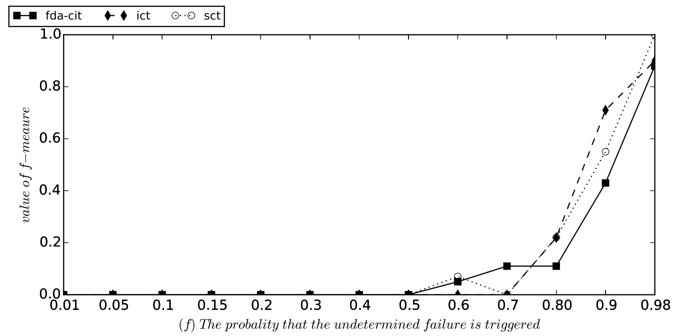


Fig. 14. F-measure for various probabilities of un-determining failure

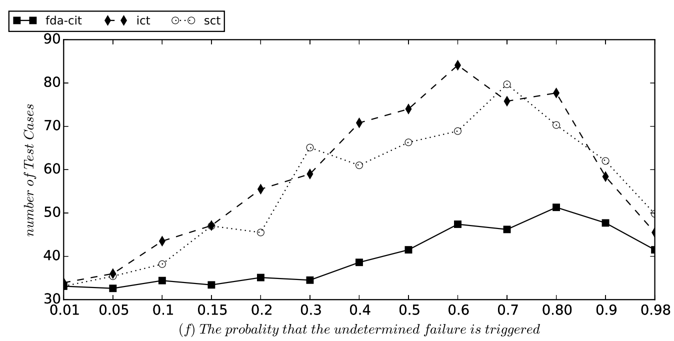


Fig. 15. Test Cases for various probabilities of un-determining failure

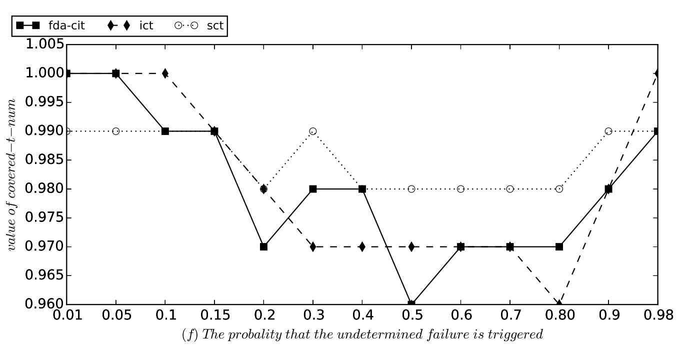


Fig. 16. The tested-t-way coverage for various probabilities of un-determining failure

TABLE XXVIII

INPUTS MODEL FOR EXPERIMENTS OF NON-SAFE VALUE

Subjects	Inputs	MFS
Syn1	4^{8}	2(6) 6(4)
Syn2	4^{10}	2(10) 6(4)
Syn3	4^{12}	2(6) 3(4) 7(4)
Syn4	4^{16}	2(2) 3(4) 5(4) 8(4)
Syn5	4^{20}	2(10) 7(4) 9(4)
Syn6	4^{25}	2(10) 9(4) 12(4)
Syn7	4^{30}	2(6) 3(4) 10(4) 15(4)
Syn8	4^{35}	2(6) 6(4) 10(4) 17(4)
Syn9	4^{40}	2(6) 8(4) 13(4) 17(4)
Syn10	4^{50}	2(6) 13(4) 15(4) 20(4)

disappear at the next time. These two statues exchanged frequently and resulted in a negative influence on the MFS identification.

The second observation is that when the probability of triggering MFS was larger than 0.5, the f-measure of all the three approaches increased. In fact, when the probability of triggering MFS was larger than 0.9, the f-measure of all the three approaches was more than 0.4. We believe if the probability was relatively high, then all the three approaches could easily detect it. Under this condition, the failure was similar to a deterministic failure, which also had little influence on the MFS identification.

With regard to the test cases, our conclusion is similar to the previous study, that is, *fda-cit* needed the smallest amount of test cases, then followed by *ict* and *sct*.

With respect to the masking effects, we can make the following observation. If the probability was too small (below 0.15) or too high (above 0.9), all the three approaches performed relatively well. This is reasonable because if the probability of triggering MFS was too small, approaches could hardly detect the failure. As a result, there are more passing test cases generated by these three approaches, and more tested-t-way schemas can be checked. On the other hand, if the probability was too high, all these three approaches could easily identify the MFS accurately. Under this condition, the results of the tested-t-way coverage obtained by these three approaches were similar to the condition for handling deterministic failure. The worst condition was in between (the probability was around 0.3 to 0.8). Under such condition, all these three approaches can neither identify the MFS accurately nor generate a large number of passing test cases.

Since the non-deterministic failures have negative effects on MFS identification, it is desirable to alleviate the effects. In this paper, we consider the redundancy of test case execution, i.e., we repeatedly run one test case to check whether it fails or not instead of just one time. We conducted an additional experiment to evaluate the performance of this strategy. Specifically, all the experimental set-ups are as the same as the previous experiment on non-deterministic failures, except that we set the redundancy of test execution to be 5 (run 5 times for each test case).

Figure 17 shows the results. From this figure, we can easily learn that for all these three approaches, there was a significant improvement in the quality of MFS identification. In fact, all these three approaches start to identify at least one MFS among 30 times even the probability of triggering MFS was as low as 0.2. Additionally, when the probability was larger than 0.4, the f-measure of all the three approaches was larger than 0.4. What's more, the f-measure of all the three approaches was close to 1 when the probability was larger than 0.5. These results indicated that the redundancy of test case execution is one potential approach to handle the non-deterministic failures problem.

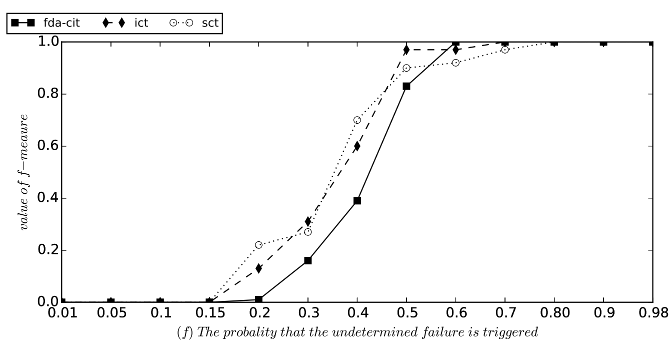


Fig. 17. F-measure for various probabilities of un-determining failure (test execution redundancy of 5)

3) Non-Safe values: The results of evaluating how well these approaches handle non-safe values are shown in Fig. 18, Fig. 19, and Fig. 20.

There are several observations about these figures. First, the non-safe values did affect the MFS identification quality of all the approaches. In fact, the f-measures of all the three approaches listed in Fig. 19 were lower than those 0.7. Specifically, *ict*'s f-measure ranged from 0.52 to 0.67, *sct*'s ranged from 0.42 to 0.64, and *fda-cit*'s ranged from 0.01 to about 0.08. Based on

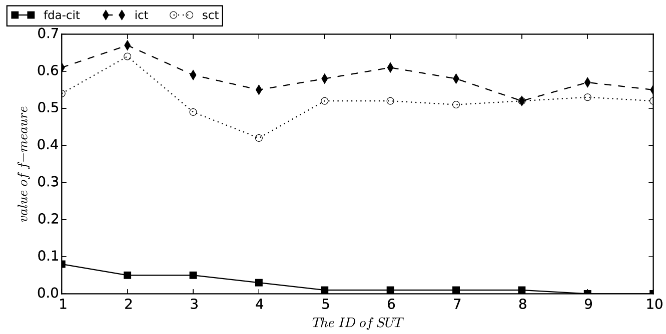


Fig. 18. F-measure for various SUTs of un-safe values

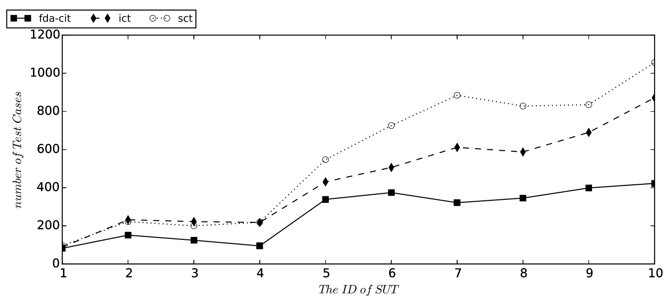


Fig. 19. Test Cases for various SUTs of un-safe values

these data, we can conclude our second observation, that is, *ict* also performed best under the condition that there are no safe values. We believe this is due to our feedback checking process, which significantly improves the quality of MFS identification, and reduces the negative effects caused by non-safe values. At last, with regard to the number of test cases, *fda-cit* still generated

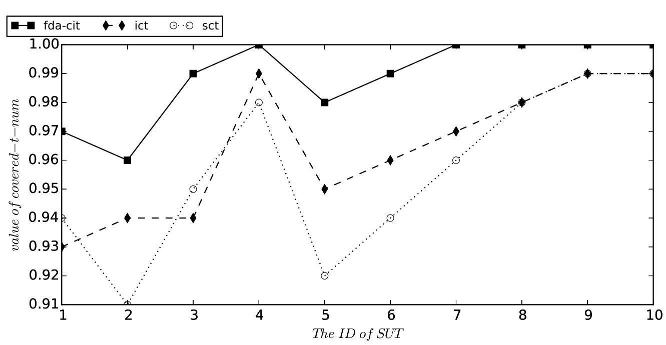


Fig. 20. The tested-t-way coverage for various SUTs of un-safe values

the fewest, but this also led to the low f-measure of MFS identification.

Concerning the masking effects, these three approaches satisfied the following relationship: *fda-cit* obtained the highest score at the tested-t-way coverage, followed by *ict*, and *sct* was the last one. In fact, this condition is similar to the condition of there is a large number of MFS in the SUT (there are many MFS so that there are no safe values in our experiments). As discussed in Section V-G2, when the number of MFS is relatively high, *fda-cit* generated more passing test cases than approaches *sct* and *ict*. Hence, *fda-cit* performed the best among the three approaches. The reason that *ict* performed better than *sct* is that *ict* identified more MFS than *sct*. As a result, *ict* obtained more schemas that satisfied the tested-t-way coverage.

Besides these observations, it is also important to figure out how many times that the effects of non-safe values were triggered. More specifically, for the approaches *ict* and *sct* which need to identify the MFS for each of the failing test cases, we need to figure out how many times when these MFS actually caused failures during the MFS identification for one specific failing test case. We listed the results in Figure 21 and Figure 22, in which Figure 21 recorded the number of total times that the non-safe MFS are triggered for each software subject, while Figure 22 recorded average number of times that the non-safe MFS are triggered for each time of MFS identification.

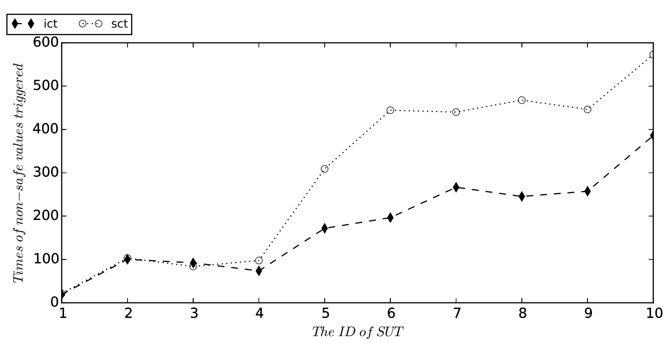


Fig. 21. The times of non-safe MFS are triggered in total for each subject

Based on these two figures (Figure 21 and 22), we can learn that for both of two approaches, the number of times that non-safe MFS was triggered was not trivial. In fact, except for the first subject, the number that non-safe MFS was triggered by these two approaches was both beyond 73.6 times for all the remaining subjects (the maximal non-safe MFS's triggered times of *sct* was up to 572.8, and for *ict*, this number was up to 385.8). Additionally, the number

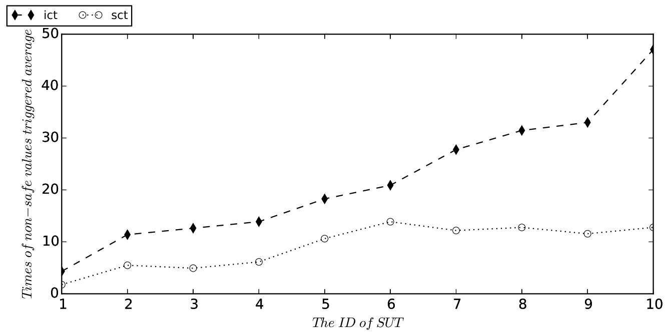


Fig. 22. The times of non-safe MFS are triggered for each time of MFS identification

that non-safe MFS was triggered for each time that MFS identification proceeded was still not small. Specifically, for each time of MFS identification, these non-safe MFS were triggered by about 22 times at average for *ict*, and 7.3 times for *sct*.

Above all, the answer to the Q7 is:

The non-deterministic failures and non-safe values do negatively affect the results of all the three approaches. Besides, concerning the condition of non-safe values, *ict* obtained the best MFS identification results and performed better than *sct* at the reduction of test cases and masking effects, while *fda-cit* generated the smallest number of test cases and obtained the highest covered-t-coverage. As for non-deterministic failures, *ict* still obtained the best MFS identification results and the second highest covered-t-coverage in most cases, *fda-cit* did the best at the reduction of test cases, while *sct* obtained the highest covered-t-coverage in most cases. Moreover, one potential solution for handling non-deterministic failures is the redundancy of test case execution.

I. Comparison with static error locating arrays

Considering that all these approaches evaluated in our previous experiments are all dynamic approaches (generating test cases), it is interesting to observe how well does the alternative way, i.e., static error locating arrays, perform on the CT problems.

Error locating array [14], [16] is a well-designed set of test cases that can support not only failure detection but also the identification of the MFS of the failure. It is known that only with a covering array sometimes is not sufficient to identify the MFS; thus additional test cases are needed. Martínez et al. [15] have proved that a $(t + d)$-way covering array can identify all the

MFS with the number of them no more than *d*, and degree no more than *t*. After executing all the test cases in the $(t + d)$-way covering array, the MFS can be obtained by keeping those t-degree or less than t-degree schemas that only appear in the failing test cases. So with the number *d* and degree *t* known in prior, a $(t + d)$-way covering array is an *Error Locating Array (ELA)*.

To compare our approach with this Error Locating Array is meaningful, as both approaches have the same target. The relationship between our approach with the Error Locating Array can be deemed as the dynamic vs. static. In detail, our approach dynamically detects and identifies the MFS in the SUT, i.e., the test cases generated by our approach are changed according to the specific MFS. On the contrary, ELA just generates a static covering array, and it can support MFS identification if the number and degree of these schemas are known in prior.

1) Study setup: In this section, we will apply ELA to identify the MFS of the 5 subjects in Table VIII. It is noted that the conclusion that a *(t + d)*-way covering array is an ELA is based on that there must exist *safe* values for each parameter of the SUT. A *safe* value is the parameter value that is not in any part of these MFS. In our experiment, all the five subject programs satisfy this condition. Based on this, we then applied ELA to generate appropriate covering arrays for each subject program and recorded the MFS identified as well as the overall test cases generated. The covering array generation algorithm we adopted in this experiment is also augmented simulated annealing approach [11], [38], and similar to previous experiments, this experiment is repeated 30 times.

2) Result and discussion: First, we list the subject information (the number of MFS d and maximal MFS degree t), together with the covering arrays that ELA needs to build, in Table XXIX.

TABLE XXIX
THE COVERING ARRAYS THAT ELA NEEDS TO BUILD FOR EACH SUBJECT

Subject	t	d	t+d	ELA
Tomcat	2	3	5	CA(N;5,10,($2^8 \times 3^1 \times 4^1$))
Hsqldb	3	3	6	CA(N;6,12,($2^9 \times 3^2 \times 4^1$))
Gcc	3	4	7	CA(N;7,10,($2^9 \times 6^1$))
Jflex	2	1	3	CA(N;3,13,($2^{10} \times 3^2 \times 4^1$))
Tcas	12	48	60	-

From this table, we can learn that for most subjects, ELA needs to build high-way covering arrays. In fact, for tcas, the CA that is needed to be built is 60-way, which is far beyond the number of parameters of TCAS (12) and hence, the corresponding covering array cannot be generated. One exception is Jflex, for which ela needs to build a 3-way covering array. It indicates that the 4-way covering arrays generated for Jflex in the previous experiments are unnecessary. From this point of view, ELA can provide an upper-bound on the strength of the covering arrays that need to be generated for one software subject.

The number of overall test cases, the quality of the identified MFS, and the results of masking effects are listed in Table XXX. We can firstly observe that this approach needs more test cases than the approaches discussed before. This is as expected because this approach needs to generate a higher-way covering array than previous approaches. Apart from the high cost, this approach correctly identified all the real MFS. The accuracy has been proved in [15], [16]. Note that this perfect MFS identification result is based on the fact that it knows the number and degree of the MFS at first, which is usually not available in practice. With respect to the masking effects, ELA nearly obtained the 100% tested-t-way (2, 3, and 4) coverage of most subjects. They do so at the cost of using significantly more tests. Additionally, in the case when the MFS is of low degrees, ELA obtained a low percentage of the tested-t-way coverage when t is relatively high (See Tested-3-way and Tested-4-way of Jflex in Table XXX).

TABLE XXX
RESULTS FROM ERROR LOCATING ARRAY

Subject	Size	Precision	Recall	F-measure	Tested-2-way	Tested-3-way	Tested-4-way
Tomcat	210.8	1	1	1	236.0 (1.0)	1424.0 (1.0)	5450.75 (0.97)
Hsqldb	588.8	1	1	1	357.0 (1.0)	2742.0 (1.0)	14136.0 (1.0)
Gcc	783.4	1	1	1	252.0 (1.0)	1536.0 (1.0)	6048.0 (1.0)
Jflex	41.8	1	1	1	473 (1.0)	4096.75 (0.95)	19224.5 (0.72)
Tcas	-	-	-	-	-	-	-

In summary, the answer to the Q8 is:

ELA gets the best quality of the MFS identification and reduction of masking effects, but it needs much more cases than all the other dynamic approaches. It also needs to know the number and degree of the MFS in prior, which limits its application in practice.

J. Threats to validity

There are two threats to validity in our empirical studies. First, our experiments are based on 5 open-source software. However, these software programs only represented some specific inputs space and specific degree or location of the MFS. To make the conclusion more general, we need to observe how these approaches performed on other inputs models with different characteristics. For this, we created a batch of synthetic input models. More specifically, for the synthetic models used in Section V-G, we consider how approaches performed under different numbers of parameters (8 to 100) instead of some specific number of parameters obtained from previous experiments. Additionally, we also consider the different numbers of MFS (1 to 90) that contained in these synthetic models instead of only 1 or 2. In Section V-H, these models are created by considering the various probabilities of triggering MFS (1% to 98%) instead of 100% or only some specific probabilities. We also considered the number of times (1 to 47) that unsafe values are introduced each time the MFS identification proceeded in the experiments. Another point that is related to the subject application is that the number of test cases needed by the proposed approach would grow linearly with the number of configuration options of the subject application under testing.

Second, there are many generation algorithms and MFS identification algorithms. In our empirical studies, we just used AETG [8] as the test case generation strategy and OFOT [6] as the MFS identification strategy. As different generation and identification algorithms may affect the performance of our proposed CT framework, especially on the number of test cases, some studies using different test case generation and MFS identification approaches are desired.

VI. RELATED WORKS

Combinatorial testing has been widely applied in practice [42], especially on domains like configuration testing [43]–[45] and software inputs testing [8], [46], [47]. A recent survey [7] comprehensively studied existing works in CT and classified them into eight categories according to the testing procedure. Based on this study, we learn that test case generation and MFS identification are two most important parts in CT studies.

Many works have been proposed for covering array generation, which can be mainly classified into the following four categories [7]: 1) greedy methods [8], [9], [13], [48], which are very fast and effective, but may consume too many test cases. 2) mathematical methods [49]–[52], which can also be extremely fast and can produce optimal test sets in some special cases, but they impose many restrictions. 3) Heuristic search techniques [11], [53]–[57], which can generate very small size of test cases, but may cost much computation time and 4) random methods [58], [59], which are extremely fast but generate more test cases than greedy approaches.

The MFS identification problem also attracts many interests in CT. These approaches for identifying MFS can be partitioned into two categories [14] according to how the additional test cases are generated: *adaptive*–additional test cases are chosen based on the outcomes of the executed tests [6], [17]–[19], [23], [25], [34], [60]or *nonadaptive*–additional test cases are chosen independently and can be executed in parallel [14]–[16], [39], [43].

Although CT has been proven to be effective at detecting and identifying the interaction failures in SUT, however, to directly apply them in practice can be inefficient and sometimes even does not work at all. Some problems, e.g., constraints of parameters values in SUT [28], [29], masking effects of multiple failures [4], [5], dynamic requirements for the strength of covering array [45], will cause difficulty to the CT process. To overcome these problems, some works try to make CT more adaptive and flexible.

JieLi [25] augmented the MFS identifying algorithm by selecting one previous passing test case for comparison, such that it can reduce some extra test cases when compared to another efficient MFS identifying algorithm [18].

S.Fouché et al., [45] introduced the notion of incremental covering array. Different from traditional covering array, it does not need a fixed strength to guide the generation; instead, it can dynamically generate high-way covering array based on existing low-way covering array, which can support a flexible tradeoff between the covering array strength and testing resources. Cohen [28], [29] studied the impacts of constraints on CT and proposed an SAT-based approach that can handle those constraints. Bryce and Colbourn [61] proposed a one-test-case-one-time greedy technique to not only generate test cases to cover all the t-degree interactions, but also prioritize them according to their importance. E. Dumlu et al., [4] developed a feedback-driven combinatorial testing approach that can assist traditional approaches in avoiding the masking effects between multiple failures. Yilmaz [5] extended that work by refining the MFS diagnosing method. Specifically, this feedback-driven approach firstly generates a t-way covering array, and after executing them, the MFS will be identified by utilizing a classification tree method. It then forbids these MFS and generates additional test cases to cover the interactions that are masked by the MFS. This process continues until all the interactions are covered. Additionally, Nie [62] constructed an adaptive combinatorial testing framework, which can dynamically adjust the inputs model, strength t of the covering array, and the generation strategy during CT process.

Our work differs from the above studies mainly in that we proposed a highly interactive framework for test case generation and MFS identification. Specifically, we do not generate a complete t-way covering array at first; instead, when a failure is triggered by a test case, we immediately terminate test case generation and turn to MFS identification. After the MFS is identified, the coverage will be updated, and the test case generation process continues.

Besides the works on fault localization in combinatorial testing, some code-based fault localization studies also show some similarities with our work. Existing code-based fault localization can be mainly classified into two categories [63]: First, *statistical* approaches [64]–[66]. These approaches utilize the coverage of statements or other program entities in the execution traces of failed and passed tests to compute suspiciousness of each statement or other program entities. Then they will rank these program entities according to their likelihood of containing the defect, i.e., the computed suspiciousness scores. These approaches are effective but may need sufficient test cases execution results. Second, *experimental* approaches [67]–[69]. By altering some inputs, code, or some other entities, these approaches can generate additional test cases. By comparing these test cases, as well as the testing outcomes, the failure-inducing parts of the test cases will be isolated. In fact, two MFS identification approaches are directly inspired by the delta debugging ideas [18], [25]. Additionally, a study [70] initially combines the MFS identification approach with code-based localization techniques to obtain a better fault isolation result.

From these works, the idea in BugEx [63] is quite similar to our approach, although they are applied to different contexts. Specifically, the main task of BugEx is to automatically run tests and experiments to systematically narrow down the failure causes. Unlike traditional fault localization approaches, this work also generates additional test cases. BugEx uses feedback from test outcomes to guide test generation and also leverages test case generation for debugging purposes. We believe that this work can guide our work to further understand the MFS and failure-causing code.

Another work which shares similar ideas comes from the Software Product Lines (SPL) testing filed [26], [71]–[73]. Many techniques in CT have been applied on SPL testing [73], among which Henard C, et al. [26] considered both test case generation and prioritizing (by selecting dissimilar tests). Also, our framework can be deemed as a solution to the test case generation and prioritization problem, which aims at fault localization as well as fault detection. As a result, it is appealing to apply our framework to the SPL testing problem. On the other hand, the idea of selecting dissimilar tests may be one potential solution to avoid multiple MFS appearing in one test case, which may improve the effectiveness of our framework.

VII. Conclusion and Future works

Combinatorial testing is an effective testing technique for detecting and diagnosis of the failure-inducing interactions in the SUT. Traditional CT separately studies test case generation and MFS identification. In this paper, we proposed a new CT framework, i.e., *interleaving CT*, which integrates these two important stages, which allows for both generation and identification better share each other's information. As a result, the interleaving CT approach can provide more efficient testing than augmented sequential CT.

Empirical studies were conducted on five open-source software subjects and several other synthetic software. The results showed that when compared to the other approaches, *ict* obtained better MFS identification results in most cases (both empirical studies on real software and empirical studies on synthetic software). *ict* also decreased the number of generated test cases when compared with *sct*, and it obtained a good result at the reduction of masking effects between different MFS even when compared to *fda-cit*. As for *fda-cit*, it generated the smallest number of test cases in most cases, especially when the number of options is large. It also obtained a good result when handling masking effects. The results obtained by *sct* of these experiments lay in between those of the other two approaches in most cases. Additionally, we learned that there are several factors that may have negative effects on these approaches, which are the large number of MFS, the non-deterministic failures (especially when the possibility of the appearance of failures ranged from 0.3 to 0.8), and the non-safe values, respectively. The feedback checking mechanism and redundancy of test case execution may help to alleviate these negative effects to some extent.

As a future work, we plan to extend our interleaving CT approach with more test case generation and MFS identification algorithms, to see the extent on which our new CT framework can enhance those different CT-based algorithms. Another interesting work is to combine the interleaving CT approach with the masking effects technique *fda-cit* [5]. By this, we believe the impacts of masking effects can be further reduced, and it can support a better quality of MFS identification.

Acknowledgment

We would like to thank anonymous referees for their suggestions and comments on this paper. This work was supported by the National Key Research and Development Plan (No. 2018YFB1003800), US National Science Foundation Award CNS-1748109, US Department of Homeland Security (DHS-14-ST-062-001), and US National Institute of Standards and Technologies Award(70NANB15H199).

References

[1] D. R. Kuhn and M. J. Reilly, "An investigation of the applicability of design of experiments to software testing," in *Software Engineering Workshop, 2002. Proceedings. 27th Annual NASA Goddard/IEEE*. IEEE, 2002, pp. 91–95.

[2] D. R. Kuhn, D. R. Wallace, and J. AM Gallo, "Software fault interactions and implications for software testing," *Software Engineering, IEEE Transactions on*, vol. 30, no. 6, pp. 418–421, 2004.

[3] S. Yoo, M. Harman, and D. Clark, "Fault localization prioritization: Comparing information-theoretic and coverage-based approaches," *ACM Transactions on Software Engineering and Methodology (TOSEM)*, vol. 22, no. 3, p. 19, 2013.

[4] E. Dumlu, C. Yilmaz, M. B. Cohen, and A. Porter, "Feedback driven adaptive combinatorial testing," in *Proceedings of the 2011 International Symposium on Software Testing and Analysis*. ACM, 2011, pp. 243–253.

[5] C. Yilmaz, E. Dumlu, M. Cohen, and A. Porter, "Reducing masking effects in combinatorialinteraction testing: A feedback drivenadaptive approach," *Software Engineering, IEEE Transactions on*, vol. 40, no. 1, pp. 43–66, Jan 2014.

[6] C. Nie and H. Leung, "The minimal failure-causing schema of combinatorial testing," *ACM Transactions on Software Engineering and Methodology (TOSEM)*, vol. 20, no. 4, p. 15, 2011.

[7] C. Nie and H. Leung, "A survey of combinatorial testing," *ACM Computing Surveys (CSUR)*, vol. 43, no. 2, p. 11, 2011.

[8] D. M. Cohen, S. R. Dalal, M. L. Fredman, and G. C. Patton, "The aetg system: An approach to testing based on combinatorial design," *Software Engineering, IEEE Transactions on*, vol. 23, no. 7, pp. 437–444, 1997.

[9] R. C. Bryce and C. J. Colbourn, "The density algorithm for pairwise interaction testing," *Software Testing, Verification and Reliability*, vol. 17, no. 3, pp. 159–182, 2007.

[10] Y.-W. Tung and W. S. Aldiwan, "Automating test case generation for the new generation mission software system," in *Aerospace Conference Proceedings, 2000 IEEE*, vol. 1. IEEE, 2000, pp. 431–437.

[11] M. B. Cohen, C. J. Colbourn, and A. C. Ling, "Augmenting simulated annealing to build interaction test suites," in *Software Reliability Engineering, 2003. ISSRE 2003. 14th International Symposium on*. IEEE, 2003, pp. 394–405.

[12] K. J. Nurmela, "Upper bounds for covering arrays by tabu search," *Discrete applied mathematics*, vol. 138, no. 1, pp. 143–152, 2004.

[13] Y. Lei, R. Kacker, D. R. Kuhn, V. Okun, and J. Lawrence, "Ipog/ipog-d: efficient test generation for multi-way combinatorial testing," *Software Testing, Verification and Reliability*, vol. 18, no. 3, pp. 125–148, 2008.

[14] C. J. Colbourn and D. W. McClary, "Locating and detecting arrays for interaction faults," *Journal of combinatorial optimization*, vol. 15, no. 1, pp. 17–48, 2008.

[15] C. Martínez, L. Moura, D. Panario, and B. Stevens, "Algorithms to locate errors using covering arrays," in *LATIN 2008: Theoretical Informatics*. Springer, 2008, pp. 504–519.

[16] C. Martínez, L. Moura, D. Panario, and B. Stevens, "Locating errors using elas, covering arrays, and adaptive testing algorithms," *SIAM Journal on Discrete Mathematics*, vol. 23, no. 4, pp. 1776–1799, 2009.

[17] X. Niu, C. Nie, Y. Lei, and A. T. Chan, "Identifying failure-inducing combinations using tuple relationship," in *Software Testing, Verification and Validation Workshops (ICSTW), 2013 IEEE Sixth International Conference on*. IEEE, 2013, pp. 271–280.

[18] Z. Zhang and J. Zhang, "Characterizing failure-causing parameter interactions by adaptive testing," in *Proceedings of the 2011 International Symposium on Software Testing and Analysis*. ACM, 2011, pp. 331–341.

[19] L. S. G. Ghandehari, Y. Lei, T. Xie, R. Kuhn, and R. Kacker, "Identifying failure-inducing combinations in a combinatorial test set," in *Software Testing, Verification and Validation (ICST), 2012 IEEE Fifth International Conference on*. IEEE, 2012, pp. 370–379.

[20] D. Jin, X. Qu, M. B. Cohen, and B. Robinson, "Configurations everywhere: Implications for testing and debugging in practice," in *Companion Proceedings of the 36th International Conference on Software Engineering*. ACM, 2014, pp. 215–224.

[21] X. Qu, M. B. Cohen, and G. Rothermel, "Configuration-aware regression testing: an empirical study of sampling and prioritization," in *Proceedings of the 2008 international symposium on Software testing and analysis*. ACM, 2008, pp. 75–86.

[22] C. Song, A. Porter, and J. S. Foster, "itree: Efficiently discovering high-coverage configurations using interaction trees," in *Proceedings of the 2012 International Conference on Software Engineering*. IEEE Press, 2012, pp. 903–913.

[23] Z. Wang, B. Xu, L. Chen, and L. Xu, "Adaptive interaction fault location based on combinatorial testing," in *Quality Software (QSIC), 2010 10th International Conference on*. IEEE, 2010, pp. 495–502.

[24] M. B. Cohen, M. B. Dwyer, and J. Shi, "Interaction testing of highly-configurable systems in the presence of constraints," in *Proceedings of the 2007 international symposium on Software testing and analysis*. ACM, 2007, pp. 129–139.

[25] J. Li, C. Nie, and Y. Lei, "Improved delta debugging based on combinatorial testing," in *Quality Software (QSIC), 2012 12th International Conference on*. IEEE, 2012, pp. 102–105.

[26] C. Henard, M. Papadakis, G. Perrouin, J. Klein, P. Heymans, and Y. Le Traon, "Bypassing the combinatorial explosion: Using similarity to generate and prioritize t-wise test configurations for software product lines," *Software Engineering, IEEE Transactions on*, vol. 40, no. 7, pp. 650–670, 2014.

[27] C. Henard, M. Papadakis, M. Harman, Y. Jia, and Y. Le Traon, "Comparing white-box and black-box test prioritization," in *Proceedings of the 38th International Conference on Software Engineering*. ACM, 2016, pp. 523–534.

[28] M. B. Cohen, M. B. Dwyer, and J. Shi, "Constructing interaction test suites for highly-configurable systems in the presence of constraints: A greedy approach," *Software Engineering, IEEE Transactions on*, vol. 34, no. 5, pp. 633–650, 2008.

[29] M. B. Cohen, M. B. Dwyer, and J. Shi, "Exploiting constraint solving history to construct interaction test suites," in *Testing: Academic and Industrial Conference Practice and Research Techniques-MUTATION, 2007.* IEEE, 2007, pp. 121–132.

[30] M. Grindal, J. Offutt, and J. Mellin, "Handling constraints in the input space when using combination strategies for software testing," 2006.

[31] L. Yu, F. Duan, Y. Lei, R. N. Kacker, and D. R. Kuhn, "Constraint handling in combinatorial test generation using forbidden tuples," in *Software Testing, Verification and Validation Workshops (ICSTW), 2015 IEEE Eighth International Conference on*. IEEE, 2015, pp. 1–9.

[32] M. Berkelaar, K. Eikland, and P. Notebaert, "lp_solve 5.5, open source (mixed-integer) linear programming system," Software, May 1 2004, last accessed Dec, 18 2009. [Online]. Available: http://lpsolve.sourceforge.net/5.5/

[33] K. Kolinko, "The HTTP Connector," http://tomcat.apache.org/tomcat-7.0-doc/config/http.html, 2014, [Online; accessed 3-Nov-2014].

[34] K. Shakya, T. Xie, N. Li, Y. Lei, R. Kacker, and R. Kuhn, "Isolating failure-inducing combinations in combinatorial

testing using test augmentation and classification," in *Software Testing, Verification and Validation (ICST), 2012 IEEE Fifth International Conference on*. IEEE, 2012, pp. 620–623.

[35] D. R. Kuhn and V. Okun, "Pseudo-exhaustive testing for software," in *Software Engineering Workshop, 2006. SEW'06. 30th Annual IEEE/NASA*. IEEE, 2006, pp. 153–158.

[36] D. Le Berre, A. Parrain *et al.*, "The sat4j library, release 2.2, system description," *Journal on Satisfiability, Boolean Modeling and Computation*, vol. 7, pp. 59–64, 2010.

[37] N. Eén and N. Sörensson, "An extensible sat-solver," in *Theory and applications of satisfiability testing*. Springer, 2004, pp. 502–518.

[38] M. B. Cohen, C. J. Colbourn, and A. C. Ling, "Constructing strength three covering arrays with augmented annealing," *Discrete Mathematics*, vol. 308, no. 13, pp. 2709–2722, 2008.

[39] J. Zhang, F. Ma, and Z. Zhang, "Faulty interaction identification via constraint solving and optimization," in *Theory and Applications of Satisfiability Testing–SAT 2012*. Springer, 2012, pp. 186–199.

[40] W. E. Wong, R. Gao, Y. Li, R. Abreu, and F. Wotawa, "A survey on software fault localization," *IEEE Transactions on Software Engineering*, vol. 42, no. 8, pp. 707–740, 2016.

[41] V. Debroy and W. E. Wong, "Insights on fault interference for programs with multiple bugs," in *Software Reliability Engineering, 2009. ISSRE'09. 20th International Symposium on*. IEEE, 2009, pp. 165–174.

[42] D. R. Kuhn, R. N. Kacker, and Y. Lei, "Practical combinatorial testing," *NIST Special Publication*, vol. 800, p. 142, 2010.

[43] C. Yilmaz, M. B. Cohen, and A. A. Porter, "Covering arrays for efficient fault characterization in complex configuration spaces," *Software Engineering, IEEE Transactions on*, vol. 32, no. 1, pp. 20–34, 2006.

[44] M. B. Cohen, J. Snyder, and G. Rothermel, "Testing across configurations: implications for combinatorial testing," *ACM SIGSOFT Software Engineering Notes*, vol. 31, no. 6, pp. 1–9, 2006.

[45] S. Fouché, M. B. Cohen, and A. Porter, "Incremental covering array failure characterization in large configuration spaces," in *Proceedings of the eighteenth international symposium on Software testing and analysis*. ACM, 2009, pp. 177–188.

[46] M. N. Borazjany, L. Yu, Y. Lei, R. Kacker, and R. Kuhn, "Combinatorial testing of acts: A case study," in *Software Testing, Verification and Validation (ICST), 2012 IEEE Fifth International Conference on*. IEEE, 2012, pp. 591–600.

[47] B. Garn and D. E. Simos, "Eris: A tool for combinatorial testing of the linux system call interface," in *Software Testing, Verification and Validation Workshops (ICSTW), 2014 IEEE Seventh International Conference on*. IEEE, 2014, pp. 58–67.

[48] R. C. Bryce, C. J. Colbourn, and M. B. Cohen, "A framework of greedy methods for constructing interaction test suites," in *Proceedings of the 27th international conference on Software engineering*. ACM, 2005, pp. 146–155.

[49] A. Hartman, "Software and hardware testing using combinatorial covering suites," in *Graph theory, combinatorics and algorithms*. Springer, 2005, pp. 237–266.

[50] N. Kobayashi, "Design and evaluation of automatic test generation strategies for functional testing of software," *Osaka, Japan, Osaka Univ*, 2002.

[51] A. W. Williams, "Determination of test configurations for pair-wise interaction coverage," in *Testing of Communicating Systems*. Springer, 2000, pp. 59–74.

[52] A. W. Williams and R. L. Probert, "Formulation of the interaction test coverage problem as an integer program," in *Testing of Communicating Systems XIV*. Springer, 2002, pp. 283–298.

[53] R. C. Bryce and C. J. Colbourn, "One-test-at-a-time heuristic search for interaction test suites," in *Proceedings of the 9th annual conference on Genetic and evolutionary computation*. ACM, 2007, pp. 1082–1089.

[54] M. B. Cohen, P. B. Gibbons, W. B. Mugridge, and C. J. Colbourn, "Constructing test suites for interaction testing," in *Software Engineering, 2003. Proceedings. 25th International Conference on*. IEEE, 2003, pp. 38–48.

[55] S. A. Ghazi and M. A. Ahmed, "Pair-wise test coverage using genetic algorithms," in *Evolutionary Computation, 2003. CEC'03. The 2003 Congress on*, vol. 2. IEEE, 2003, pp. 1420–1424.

[56] T. Shiba, T. Tsuchiya, and T. Kikuno, "Using artificial life techniques to generate test cases for combinatorial testing," in *Computer Software and Applications Conference, 2004. COMPSAC 2004. Proceedings of the 28th Annual International*. IEEE, 2004, pp. 72–77.

[57] H. Wu, C. Nie, F.-C. Kuo, H. Leung, and C. J. Colbourn, "A discrete particle swarm optimization for covering array generation," *Evolutionary Computation, IEEE Transactions on*, vol. 19, no. 4, pp. 575–591, 2015.

[58] P. J. Schroeder, P. Bolaki, and V. Gopu, "Comparing the fault detection effectiveness of n-way and random test suites," in *Empirical Software Engineering, 2004. ISESE'04. Proceedings. 2004 International Symposium on*. IEEE, 2004, pp. 49–59.

[59] C. Nie, H. Wu, X. Niu, F.-C. Kuo, H. Leung, and C. J. Colbourn, "Combinatorial testing, random testing, and adaptive random testing for detecting interaction triggered failures," *Information and Software Technology*, vol. 62, pp. 198–213, 2015.

[60] L. Shi, C. Nie, and B. Xu, "A software debugging method based on pairwise testing," in *Computational Science–ICCS 2005*. Springer, 2005, pp. 1088–1091.

[61] R. C. Bryce and C. J. Colbourn, "Prioritized interaction testing for pair-wise coverage with seeding and constraints," *Information and Software Technology*, vol. 48, no. 10, pp. 960–970, 2006.

[62] C. Nie, H. Leung, and K.-Y. Cai, "Adaptive combinatorial testing," in *Quality Software (QSIC), 2013 13th International Conference on*. IEEE, 2013, pp. 284–287.

[63] J. Röβler, G. Fraser, A. Zeller, and A. Orso, "Isolating failure causes through test case generation," in *Proceedings of the 2012 International Symposium on Software Testing and Analysis*. ACM, 2012, pp. 309–319.

[64] J. A. Jones, M. J. Harrold, and J. Stasko, "Visualization of test information to assist fault localization," in *Proceedings of the 24th international conference on Software engineering*. ACM, 2002, pp. 467–477.

[65] B. Liblit, A. Aiken, A. X. Zheng, and M. I. Jordan, "Bug isolation via remote program sampling," *ACM SIGPLAN Notices*, vol. 38, no. 5, pp. 141–154, 2003.

[66] C. Liu, X. Yan, L. Fei, J. Han, and S. P. Midkiff, "Sober: statistical model-based bug localization," in *ACM SIGSOFT Software Engineering Notes*, vol. 30, no. 5. ACM, 2005, pp. 286–295.

[67] A. Zeller and R. Hildebrandt, "Simplifying and isolating failure-inducing input," *Software Engineering, IEEE Transactions on*, vol. 28, no. 2, pp. 183–200, 2002.

[68] A. Zeller, "Yesterday, my program worked. today, it does not. why?" in *Software EngineeringESEC/FSE99*. Springer, 1999, pp. 253–267.

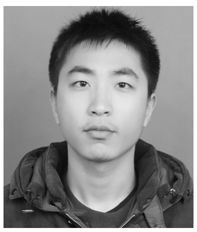
[69] G. Misherghi and Z. Su, "Hdd: hierarchical delta debugging," in *Proceedings of the 28th international conference on Software engineering*. ACM, 2006, pp. 142–151.

[70] L. S. Ghandehari, Y. Lei, D. Kung, R. Kacker, and R. Kuhn, "Fault localization based on failure-inducing combinations," in *Software Reliability Engineering (ISSRE), 2013 IEEE 24th International Symposium on*. IEEE, 2013, pp. 168–177.

[71] G. Perrouin, S. Sen, J. Klein, B. Baudry, and Y. Le Traon, "Automated and scalable t-wise test case generation strategies for software product lines," in *Software Testing, Verification and Validation (ICST), 2010 Third International Conference on*. IEEE, 2010, pp. 459–468.

[72] R. E. Lopez-Herrejon, J. Javier Ferrer, F. Chicano, E. N. Haslinger, A. Egyed, and E. Alba, "A parallel evolutionary algorithm for prioritized pairwise testing of software product lines," in *Proceedings of the 2014 conference on Genetic and evolutionary computation*. ACM, 2014, pp. 1255–1262.

[73] R. E. Lopez-Herrejon, S. Fischer, R. Ramler, and A. Egyed, "A first systematic mapping study on combinatorial interaction testing for software product lines," in *Software Testing, Verification and Validation Workshops (ICSTW), 2015 IEEE Eighth International Conference on*. IEEE, 2015, pp. 1–10.



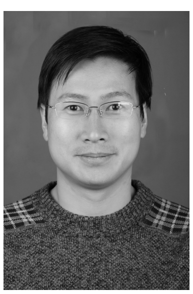
Xintao Niu born in 1988, received his B.S degree from Nanjing University of Science and Technology. He is currently working toward the PhD degree in the Department of Computer Science and Technology at Nanjing University. His Research interest is software testing, especially on combinatorial testing and fault diagnosis. His work is supervised by Dr. Nie.

Changhai Nie A Professor of Software Engineering in National Key Laboratory for Novel Software Technology and Department of Computer Science and Technology at Nanjing University. His research interest is software testing and search base software engineering, especially in combinatorial testing, search based software testing, software testing methods comparison and combination and et al.

Hareton Leung received the PhD degree in computer science from University of Alberta. He is an associate professor and the director at the Laboratory for Software Development and Management in the Department of Computing, the Hong Kong Polytechnic University. He currently serves on the editorial board of Software Quality Journal and Journal of the Association for Software Testing. His research interests include software testing, software maintenance, quality and process improvement, and software metrics

Jeff Y. Lei is a full professor in Department of Computer Science and Engineering at the University of Texas, Arlington. He received his Bachelor's degree from Wuhan University (Special Class for Gifted Young), his Master's degree from Institute of Software, Chinese Academy of Sciences, and his PhD degree from North Carolina State University. He was a Member of Technical Staff in Fujitsu Network Communications, Inc. for about three years. His research is in the area of automated software analysis, testing and verification, with a special interest in software security assurance at the implementation level.

Xiaoyin Wang born in Harbin, Heilongjiang Province, China in 1984. From September 2006 to January 2012, he was a Ph.D. candidate in the Software Engineering Institute (SEI) of Peking Univerisity. His advisor is Prof. Hong Mei, and he also did research under the supervision of Prof. Lu Zhang and Prof. Tao Xie. From Oct 2008 to Sept 2009, he visited Singapore Management University as a research fellow, where he worked with Prof. David Lo. In Jan. 2012, he began to work with Prof. Dawn Song, as a PostDoc in UC Berkeley. In August 2013, he joined the computer science department of University of Texas at San Antonio.



Jiaxi Xu born in 1972, Senior Engineer in School of Information Engineering of Nanjing Xiaozhuang University. His research interest is software testing, especially embedded software testing and open source software testing.

Yan Wang received the MS degree in Control Theory and Control Engineering from University of Electronic Science and Technology of China. She is currently a lecturer in the School of Information Engineering at Nanjing Xiaozhuang University. Her research interests include development and testing of embedded software, and combinatorial interaction testing.