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

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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 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

1 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.

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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, that 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 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 makes no sense for the further failure detection. For the failure-inducing identification module, we augment it by achieving 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 needs fewer test cases than traditional CT.

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 an 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 to evaluate our new framework. These studies consist of two comparisons. The first one is to compare our new framework with the traditional one, 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. The results show that, in terms of test case generation and failure-inducing interactions identification, our approach can significantly reduce the overall needed test cases and as a result it can more quickly identify the failure-inducing interactions of the system under test.

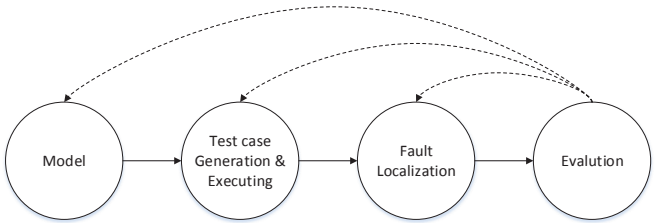

Fig. 1. The life cycle of CT

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 2 presents the preliminary background of CT. Section 3 presents a motivating example. Section 4 describes our new framework and a simple case study is also given. Section 5 presents the empirical studies and discusses the results. Section 6 shows the related works. Section 7 concludes the paper and proposes some further work.

2 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 a *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.

2.1 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 1
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 1 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], [9], [10].

2) A set of test cases one time: This strategy generates a set of test cases at each iteration. Through 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.

2.2 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], [15], [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 1 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. So in this paper, we only focus on the MFS identification. 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 2. 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 2, as test case t failed, we mutate one factor

TABLE 2
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

of test case t one time to generate new 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 mutate 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 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], [18], [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 2, we can determine that the additional test case contains the same MFS in the original failing test case, e.g., t in Table 2.

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".**

3 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], [21], [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 SQL* and *Statement Type*. The possible values each option can take on are shown in Table 3. Based on the report in the bug tracker of HSQLDB [2], an *incompatible exception* will be triggered if a *parameterised sql* is executed as *prepared statement* by HSQLDB. Hence, when option $parameterisedSQL$ is set to be *true* and $Statmetent$ 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 3
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 4 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

1. More details in: http://gist.nju.edu.cn/doc/ict/
2. For details, see: http://sourceforge.net/p/hsqldb/bugs/1173/
3. For details, see: http://hsqldb.org/doc/guide/guide.html

$parameterisedSQL$ and $Statement$, the symbol is up to 1). According to Table 4, 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 with 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, 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 on 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).

TABLE 4
Sequential CT process

		test case				Outcome
		o_1	o_2	o_3	o_4	
Generation (Execution)	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 on 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 $parameterisedSQL$ being set to *true* and $Statmetent$ to *preparedStatement*. More shortcomings of the sequential CT are discussed as follows:

3.1 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 4, 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 4, 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.

3.2 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 can not identify a valid schema in this case. For example, there are two MFS in t_4 in Table 4, 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.

3.3 Masking effects

When considering a single execution of the test set, traditional covering array usually offer an 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 4, 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 ($ScrollType$ 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 an 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 4, 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. After all, 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 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 the *masking effects* are actually caused by the *multiple MFS problem* we discussed previously. But 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.

3.4 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 4, 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 4 will evolve into the process shown in Table 5.

In Table 5, the only difference from Table 4 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 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, and 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 2 test cases 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.

TABLE 5
Augmented Sequential CT process

		o_1	o_2	o_3	o_4	Outcome
	Generation (Execution)					
	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

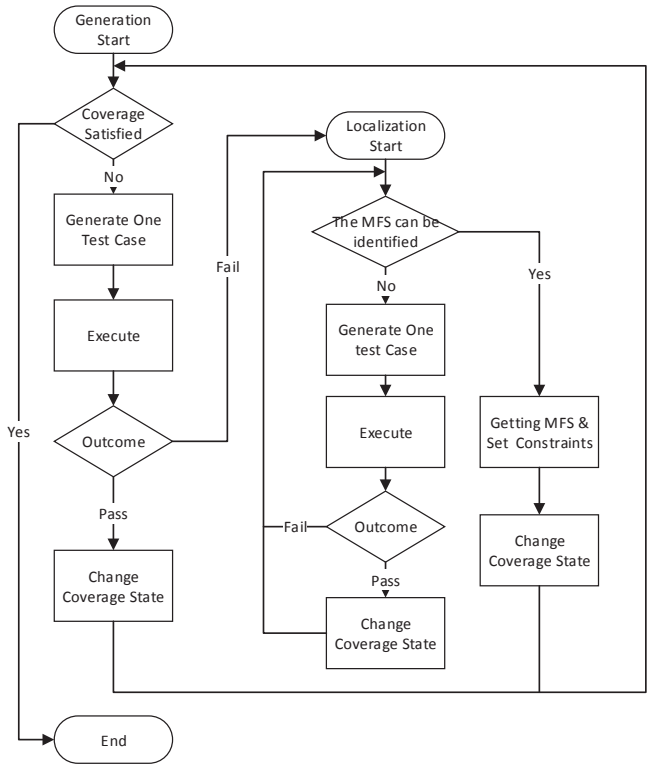

Fig. 2. The Interleaving Framework

4 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 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 3.

4.1 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.

4.2 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.

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

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.

As discussed in Section 3, 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.

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

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 4, 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.

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

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 4, 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.

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

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 on 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).

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

(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.

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

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**

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.

4.2.1 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 a 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 an 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], [18], [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.

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

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), 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. But 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 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 10 in Section 5.2).

4.2.2 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], [29], [30], [31]. 2) dynamic method, that is, it does not initially know which are constraints, but identify them as MFS and forbidden 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 3. 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 3, 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.

4.3 Advantages of our framework

In view of the problems listed in Section 3, 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, follow-

ing 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 3, 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 3, 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 a 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 generated 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.

4.4 Demonstration on an example

Applying the new framework to the scenario of Section 3, we can get the result listed in Table 6.

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.

TABLE 6
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						

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, -), etc, 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 4, and equal to the augmented sequential CT approach in Table 5. 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 7 shows how *ict* works in this condition.

TABLE 7
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 7, 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 2.2 (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).

5 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 3. 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 different number of MFS and different number of options in SUT?

Q7: How well does our approach perform when the two assumptions listed in Section 2 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).

5.1 Subject programs

The five subject programs used in our experiments are listed in Table 8. 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 8
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; and Tcas is a module of an aircraft collision avoidance system. We select these software 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 target of our empirical studies is to compare the ability of fault defection 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.

5.1.1 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 8, 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 9.

TABLE 9
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 you can only process with the "*next()*" method in a non-scrollable result set.

5.2 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 augmenting 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.

5.2.1 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 on 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

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

5.2.2 Result and discussion

Table 10 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.

One observation from this table is that the number of test cases generated by our approach was smaller than that of the *sct* approach. In fact, except for subject *Gcc*, our 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). But 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 11. 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 low-wise 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 low-wise 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 3.2).

Additionally, Table 12 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.

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*.**

5.3 Alleviation of the three problems

Section 3 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.

5.3.1 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.

TABLE 10
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

TABLE 11
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

TABLE 12
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

5.3.2 Result and discussion

1) **Redundant 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 in 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 an 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 increasing 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 13, which lists the number of test cases (on average for the repeated 30 experiments) that contain more than one MFS.

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

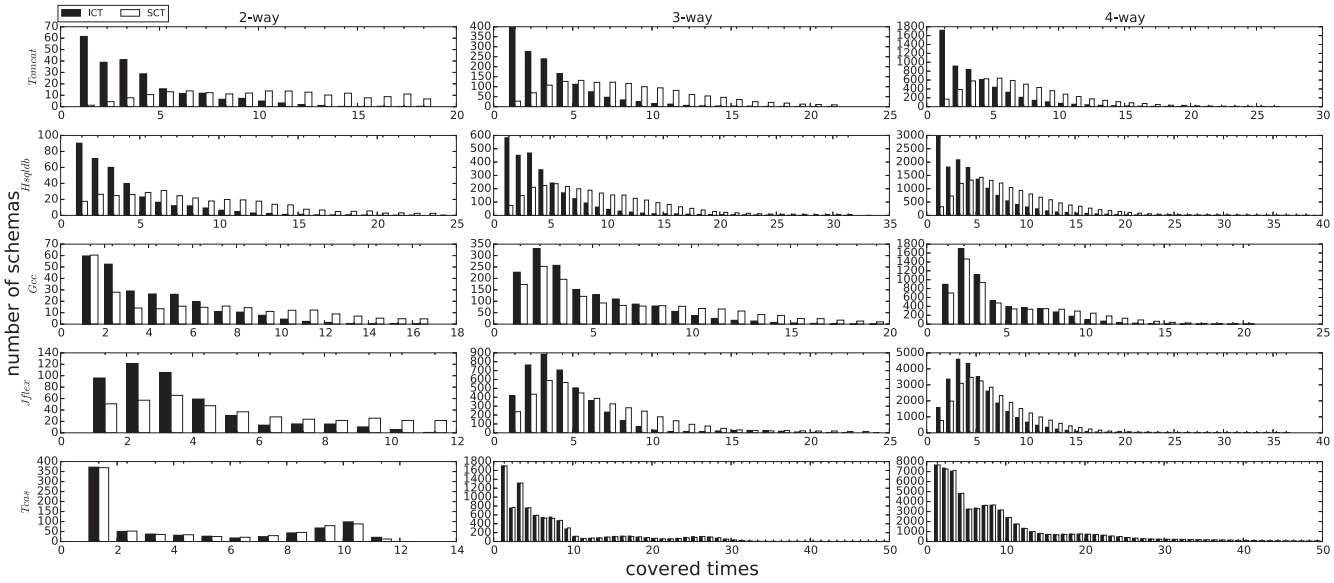

Fig. 3. The redundancy of test cases

TABLE 13
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

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 9) and the MFS of *Tcas* are all high degrees which are hardly detected.

3) **Masking effects**.

The results of masking effect for each approach is shown in Table 14. 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 the 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 3, and when compared to *sct*, *ict* is a better approach to resolve these issues. Additionally, both *ict* and *sct* have a good performance on reducing the masking effects.**

5.4 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.

5.4.1 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 on testing the five subjects listed in Table 8 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*.

5.4.2 Result and discussion

We list the results of the number of test cases generated by *ict-nonfb* in Table 15, the f-measure of MFS identification in Table 16, the average number of test cases containing multiple MFS in Table 17, and the tested-t-way coverage

TABLE 14
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%)

in Table 18. 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 15
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)

TABLE 16
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 17
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)

TABLE 18
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%)

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 ranged from 1.9 to 23.3 number of test cases. 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.

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

5.5 Comparison with 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.

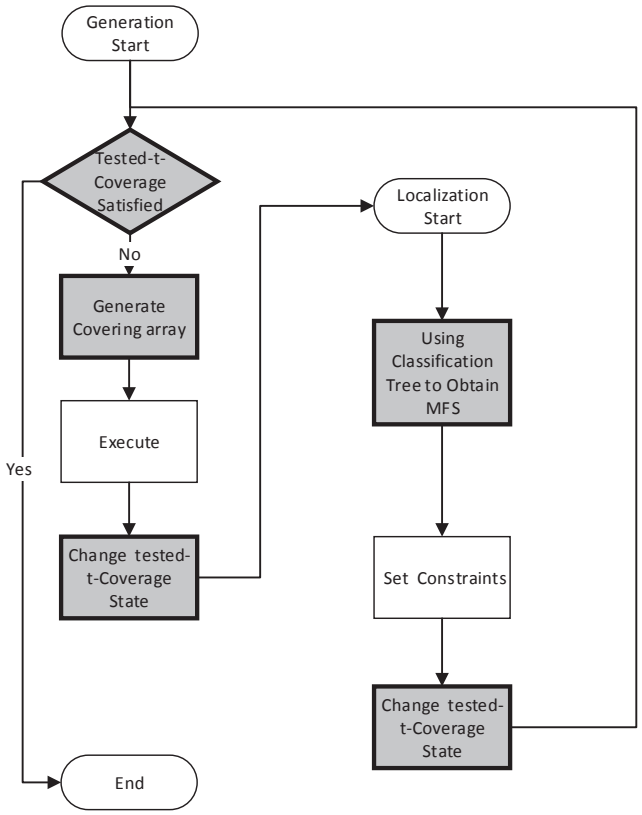

Fig. 4. The Framework of fda-cit

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 a 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.

5.5.1 Study setup

The design of this case study is similar to the previous two. For each subject in Table 8, 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 augmenting simulated annealing approach [11], [38] to build covering array for the *FDA-CIT*.

5.5.2 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 19. 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.

From this table, one observation is that *fda-cit* was better than *sct* at 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 20. 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*).

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

TABLE 19
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)

TABLE 20
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%)

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 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*.

4)**Test Cases containing multiple MFS**

Table 21 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. But 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 increasing 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.

TABLE 21
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)

5)**Masking effects**. The result is listed in Table 22, which shows the results of *tested-t-way* 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 22, 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 on 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.

To summarize, the answer to **Q4** is that **when compared to the adaptive CT approach *fda-cit*, our approach *ict* performed more effectively, especially at the quality of MFS identification and reduction of masking effects, while there are no apparent differences between them at the cost (the number of test cases). This also indicates that *ict* is a more efficient approach.**

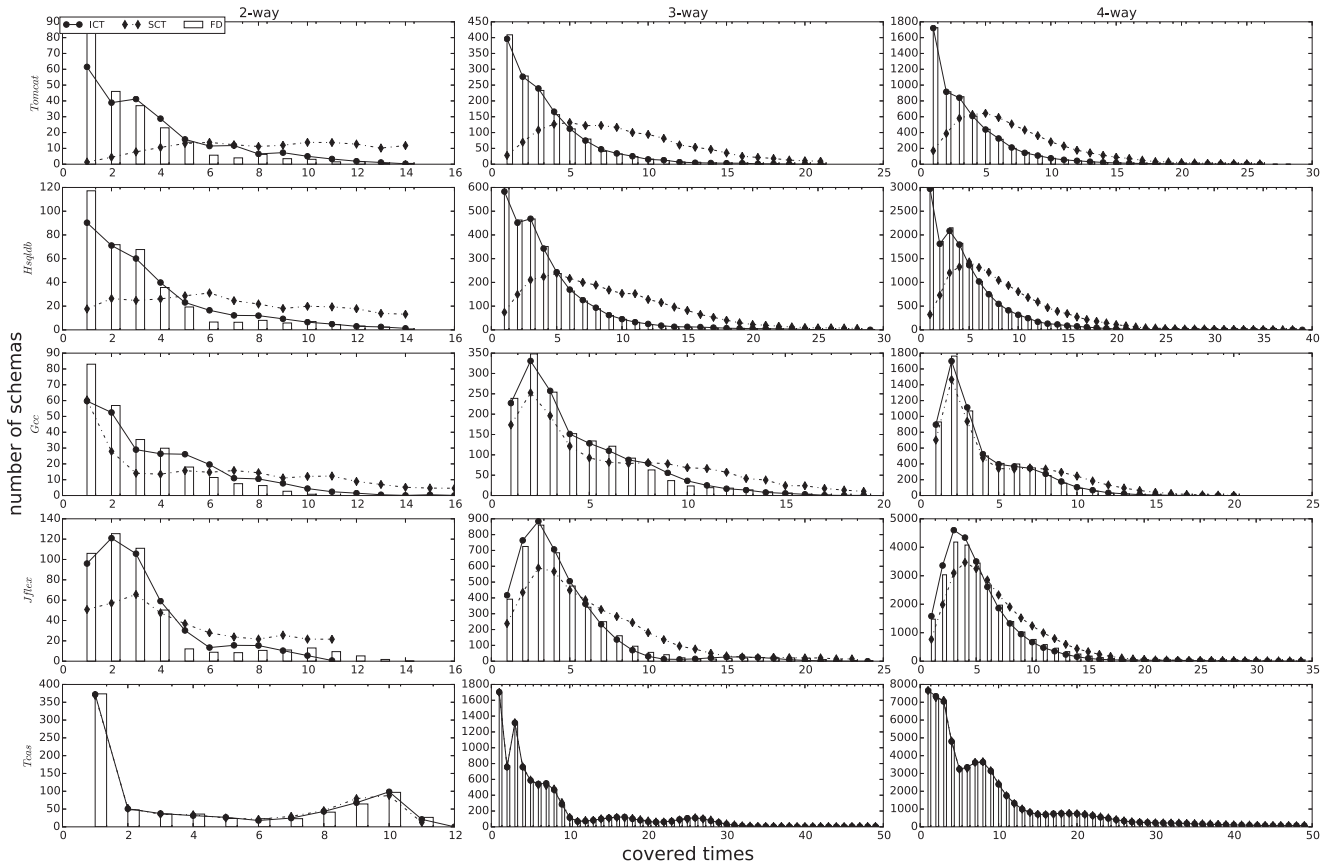

Fig. 5. The redundancy of test cases generated by *fda-cit*

TABLE 22
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%)

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, *cit* 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. Under this case, *fda-cit* needs a smaller amount of test cases [5].

5.6 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 between 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.

5.6.1 Study setup

The software subjects with multiple bugs used in this experiment are listed in Table 23. 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.

For each subject, 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 defeat, we only labeled the test cases failed with this specific

TABLE 23
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)

defeat as *fail*, and labeled other test cases (either passed after execution or failed with other defeats) as *pass*.

5.6.2 Result and discussion

We list the results of the number of test cases generated in this experiment in Table 24, the f-measure of MFS identification in Table 25, the average number of test cases containing multiple MFS in Table 26, and the tested-t-way coverage in Table 27.

TABLE 24
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
	fd	21.0	196.2	170.2
hsqldb 2.25	ict	40.4	56.0	101.2
	sct	42.0	87.8	171.2
	fd	22.8	50.6	115.2
hsqldb 2.29	ict	48.2	77.6	122.6
	sct	40.0	88.4	186.2
	fd	39.4	51.2	115.4
Jflex 1.4.1	ict	45.4	71.4	131.8
	sct	61.2	120.8	247.6
	fd	22.8	61.2	163.4
Jflex 1.4.2	ict	68.0	72.4	145.6
	sct	53.6	108.4	232.0
	fd	30.2	61.8	156.4

TABLE 25
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
	fd	0.04	0.25	0.15
hsqldb 2.25	ict	0.93	1.0	1.0
	sct	0.86	0.72	0.56
	fd	0.23	0.04	0.0
hsqldb 2.29	ict	0.52	0.81	0.84
	sct	0.4	0.57	0.53
	fd	0.17	0.17	0.19
Jflex 1.4.1	ict	1.0	1.0	1.0
	sct	0.88	0.92	0.96
	fd	0.1	0.0	0.0
Jflex 1.4.2	ict	0.76	1.0	1.0
	sct	0.96	0.72	0.72
	fd	0.16	0.0	0.0

There are several observations in the experiments with multiple defeats:

1) The results of the number of test cases satisfied the following relationship: *fda-cit* generated the smallest number of test cases, and the second best was *ict*, while the last one is *sct*. Specifically, *fda-cit* reduced 20.36 test cases on average at 2-way coverage when compared with the approach *sct*, and 19.2 test case at 3-way coverage, and 65.7 test cases at 4-way coverage. *fda-cit* also reduced about 20.6 test cases when compared to *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 about 21.9 and 66.4 test cases at 3-way and 4-way coverage, respectively, when compared to *sct*. These two approaches generated almost the same number of test cases at 2-way coverage.

TABLE 26
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
	fd	0.4	2.6	4.0
hsqldb 2.25	ict	0.8	0.8	0.4
	sct	0.6	2.2	7.0
	fd	0.6	3.2	7.6
hsqldb 2.29	ict	1.4	1.8	2.2
	sct	1.4	5.8	17.6
	fd	5.0	9.0	16.4
Jflex 1.4.1	ict	1.0	1.0	1.0
	sct	4.6	12.4	26.2
	fd	2.2	6.6	17.4
Jflex 1.4.2	ict	1.0	1.0	0.2
	sct	0.6	3.6	9.8
	fd	1.0	3.0	9.0

2) With respect to the quality of MFS identification, these three approaches satisfied the following relationship: *ict* obtained the highest score at MFS identification, following 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, and the second best approach was *fda-cit*, while the last one was *sct*. Specifically, *ict* reduced about 1.0 test cases (containing multiple MFS) at the 2-way coverage when compared with *fda-cit*, 3.84 test cases at the 3-way coverage, and 10.04 test cases at the 4-way coverage. For *fda-cit*, it reduced about 0.2 test cases at the 3-way coverage when compared with *sct*, and 2.52 test cases at the 4-way coverage (These two approaches generated a similar number of test cases that containing multiple schemas at 2-way coverage).

4) With respect to the tested-t-way coverage, these three approaches satisfied the following relationship: *fda-cit* covered the most number of tested-t-way schemas, following by approaches *sct* and *ict*, respectively. In fact, except for the

TABLE 27
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%)
	fd	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%)
	fd	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%)
	fd	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%)
	fd	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%)
	fd	269.2(56.91%)	2241.8(52.35%)	14309.2(53.93%)

2-way coverage at which *fda-cit* and *ict* covered almost the same number of tested-t-way schemas, *fda-cit* outperformed the other two approaches at 3-way and 4-way coverage. Specifically, *fda-cit* increased the tested-3-way coverage by 20% and 16%, when compared with approaches *ict* and *sct*, respectively, and increased the tested-4-way coverage by 38% and 16%, respectively. Above all, the answer to Q5 is:

Most results matched pretty well with the results obtained from the experiments of a single defeat. Particularly, *ict* performed better at MFS identification and reducing the number of test cases that containing multiple MFS, while *fda-cit* generated the least number of test cases and covered the most number of tested-t-way schemas.

5.7 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 number of MFS in the SUT and different number of options in the SUT on three approaches, i.e., *ict*, *sct*, and *fda-cit*.

5.7.1 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 number 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 number of 2-degree MFS: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20, 30, 40, 50, 60, 70, 80 and 90. 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 (MFS identification quality and cost) of each approach were collected and analysed.

The second study is to evaluate the performance of approaches under the different number of options. Hence we used synthetic subjects with the following number of options (8, 9, 10, 12, 16, 20, 30, 40, 50, 60, 70, 80, 90, 100). 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.

5.7.2 Number of MFS

The results for the sensitivity of the number of MFS are shown in Figure 6 and 7, of which the first figure focuses on the quality of MFS identification, and the second figure shows the cost.

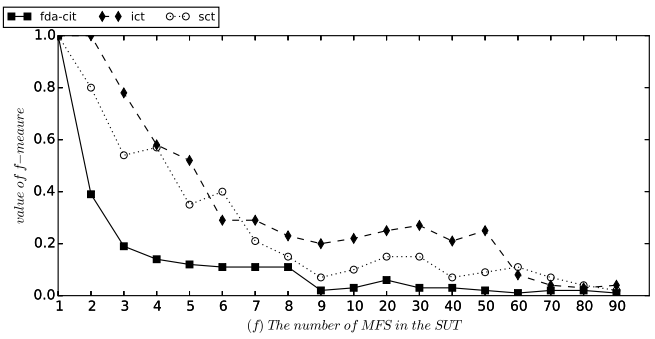

Fig. 6. F-measure for various number of MFS

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

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*,

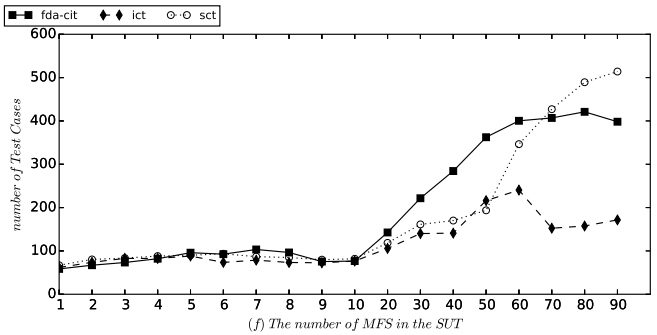

Fig. 7. Test Cases for various number of MFS

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*.

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 8. 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 9. 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).

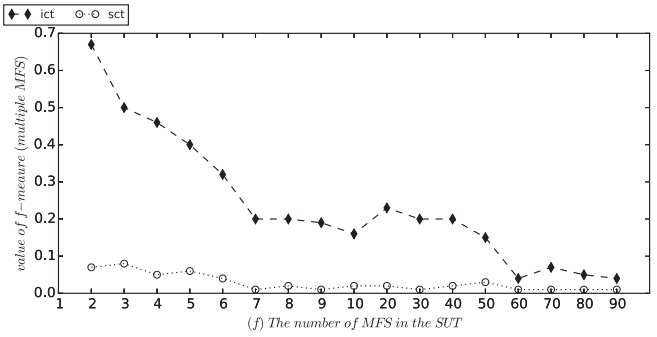

Fig. 8. F-measure (multiple MFS in one test case) for various number of MFS

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 8, *ict* obtained

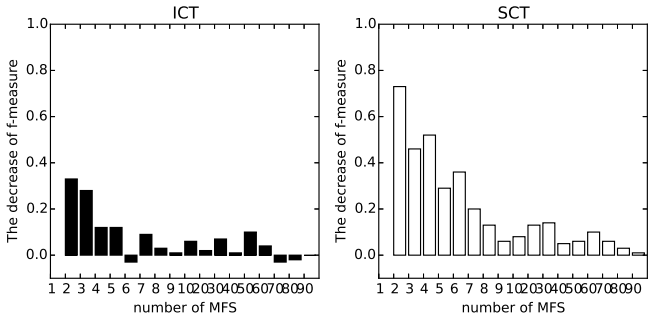

Fig. 9. The decrease of F-measure (multiple MFS in one test case) for various number of MFS

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 are ranged from 0.05 to 0.69, which is not trivial. Second, the condition that multiple MFS appear in one test case has large 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) is ranged from 0.01 to 0.73, while the decrease of f-measure of *ict* is 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.

5.7.3 Number of options

The results for the sensitivity of the number of options are shown in Fig. 10 and Fig. 11, which depicts the quality of MFS identification and the number of generated test cases, respectively.

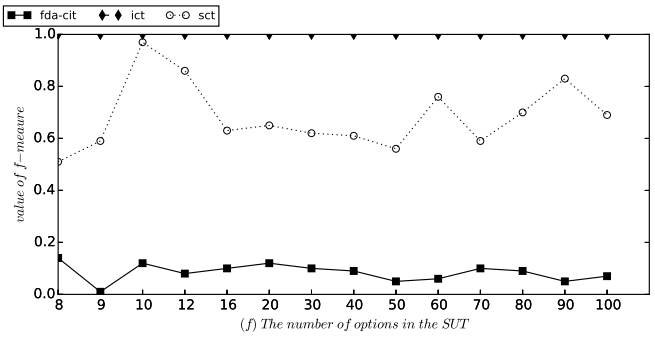

Fig. 10. F-measure for various number of options

With regard to the quality of MFS identification, it is clear that *ict* performed the best, then followed *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 to the previous study, indicating that *ict* can accurately identify the MFS, even though when the number of options is large.

Another observation about the MFS identification is that there was no clear correlation between the MFS quality

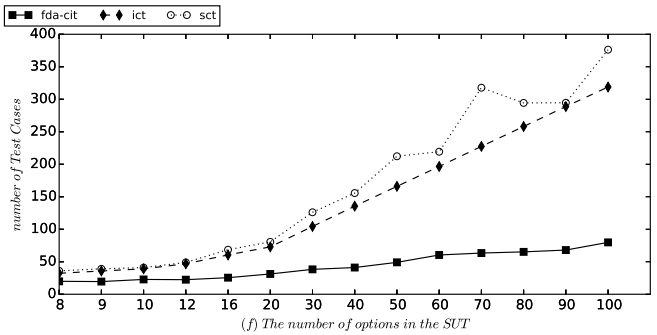

Fig. 11. Test Cases for various number of options

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 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. The complexity can be further reduced (O(log N) [17], [18], [25]). The last one was *sct*, of which the number of test cases was always larger than that of *ict*.

Therefore, the number of options in the SUT did not have 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 precision and recall of MFS identification.

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, *ict* performs best among the three approaches for various number of MFS and options.**

5.8 The ability of handling assumptions

The last study is designed to evaluate the performances of the three approaches when the two assumptions proposed on Section 2.2, i.e., deterministic failures and the existence of safe values, do not hold.

5.8.1 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 extent 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. We repeated the experiment 30 times for each probability to avoid the random affects. 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 none 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 28. The same as Table 9, 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. 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.

TABLE 28
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)

5.8.2 Non-deterministic failures

The results of evaluating the approaches on non-deterministic failures are shown in Fig. 12 and Fig. 11, of which the first figure depicts the quality of MFS identification with various probabilities that the non-deterministic failures are triggered, while the second figure shows the number of test cases.

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

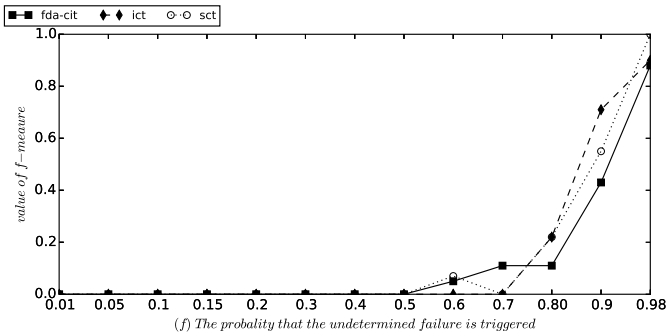

Fig. 12. F-measure for various probability of un-determining failure

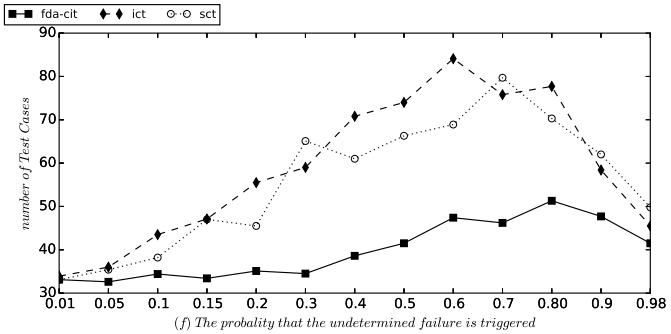

Fig. 13. Test Cases for various probability of un-determining failure

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 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 the *ict* and *sct*.

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 14 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.

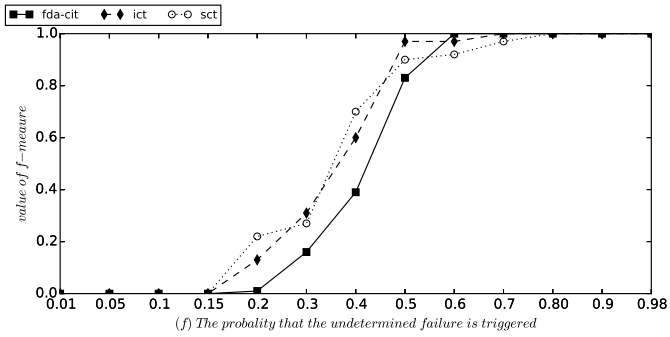

Fig. 14. F-measure for various probability of un-determining failure (test execution redundancy of 5)

5.8.3 Non Safe values

The results of evaluating the approaches on non-safe values are shown in Fig. 15 and Fig. 16.

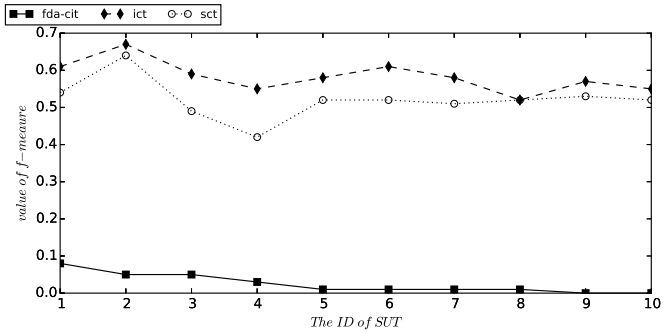

Fig. 15. F-measure for various number of un-safe values

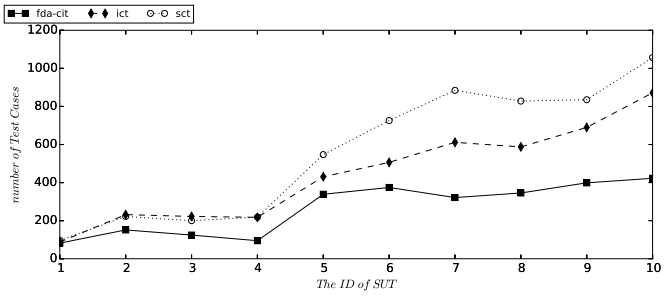

Fig. 16. Test Cases for various number of un-safe values

There are several observations about these two 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. 16 were lower than those 0.7. Specifically, *ict*'s f-measure is 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 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 the fewest, but this also led to the low f-measure of MFS identification.

Besides these observations, it's 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 17 and Figure 18, in which Figure 17 recorded the number of total times that the non-safe MFS are triggered for each software subject, while Figure 18 recorded average number of times that the non-safe MFS are triggered for each time of MFS identification.

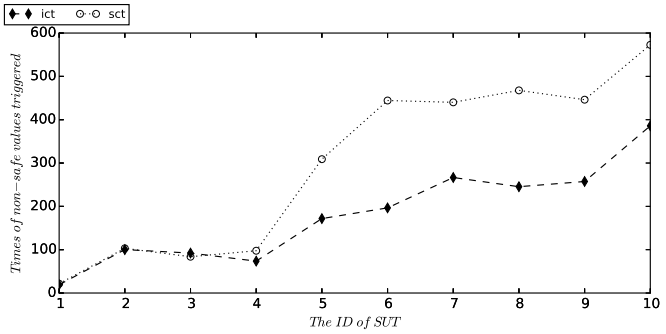

Fig. 17. The times of non-safe MFS are triggered in total for each subject

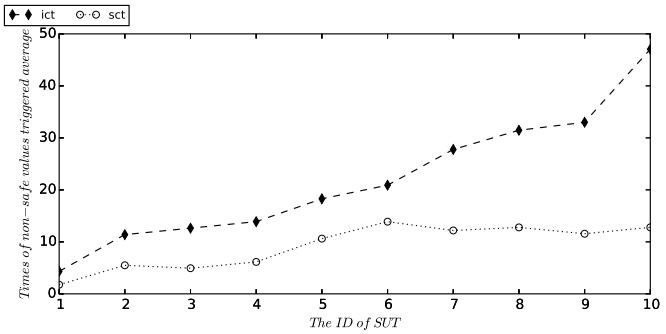

Fig. 18. The times of non-safe MFS are triggered for each time of MFS identification

Based on these two figures (Figure 17 and 18), 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 that non-safe MFS was triggered for each time that MFS identification was 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. Due to the feedback checking process, *ict* can alleviate impacts of the non-safe values. While for non-deterministic failures, one potential solution is the redundancy of test case execution.

5.9 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.

5.9.1 Study setup

In this section, we will apply ELA to identify the MFS of the 5 subjects in Table 8. 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 augmenting simulated annealing approach [11], [38], and similar as previous experiments, this experiment is repeated 30 times.

5.9.2 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 29.

TABLE 29
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 and the quality of the identified MFS are listed in Table 30. We can firstly observe that this approach needs more test cases than the approaches discussed before. This is as expected becasue 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.

TABLE 30
Results from Error Locating Array

Subject	Size	Precision	Recall	F-measure
Tomcat	210.8	1	1	1
Hsqldb	588.8	1	1	1
Gcc	783.4	1	1	1
Jflex	41.8	1	1	1
Tcas	-	-	-	-

In summary, the answer to the Q8 is:

ELA gets the best quality of the MFS identification but 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.

5.10 Threats to validity

There are two threats to validity in our empirical studies. First, our experiments are based on only 5 open-source software. More subject programs are desired to make the results more general, such that the conclusion of our experiment can reduce the impact caused by specific input space and specific degree or location of the MFS.

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.

6 RELATED WORKS

Combinatorial testing has been widely applied in practice [42], especially on domains like configuration testing [43], [44], [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], [50], [51], [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], [54], [55], [56], [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], [18], [19], [23], [25], [34], [60]or *nonadaptive*–additional test cases are chosen independently and can be executed in parallel [14], [15], [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 requirement 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 an 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], [65], [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], [68], [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 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], [72], [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 on 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.

7 Conclusion and Future works

Combinatorial testing is an effective testing technique at 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*, that 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 a more efficient testing than augmented sequential CT.

Empirical studies were conducted on five open-source software subjects. The results show that with our new CT framework, there is a reduction on the number of generated test cases when compared to the augmented sequential CT approach, while there is a significant improvement in the quality of the identified MFS. Further, when compared with another adaptive CT framework *fda-cit* [4], [5], our approach also performed better, especially with the better quality of the MFS identification. At last, we showed that our approach *ict* can still perform well on the subjects with various number of options, MFS, and on the condition that there are non-deterministic failures and non-safe values.

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.

Appendix A
The detail of the Algorithms of SCT, Augmented SCT, and ICT

A.1 the algorithm of SCT

The inputs of Algorithm 3 are information of parameters of the SUT, the strength of the covering array, and constraints. The output is the MFS. In this algorithm, SCT firstly generates a covering array using simulated Annealing algorithm [11] (line 2). It then executes each test case contained in this algorithm and collects the failing test case set T_{fail} (line 3). For each failing test case in this set, SCT uses OFOT [6] to identifies the MFS in it (line 4 to 7). At last, SCT returns all the identified MFS (line 8).

A.2 the algorithm of the augmented SCT

Algorithm 4 is similar to Algorithm 3, except that it needs to consider the previously identified MFS. Specifically, for

Algorithm 3 The overall procedure of SCT

Input: $Param$ ▷ the parameter values of the SUT
τ ▷ the strength of the covering array
$Constraints$ ▷ The constraints of SUT
Output: MFS ▷ The MFS of SUT
1: $MFS \leftarrow \emptyset$
2: $T \leftarrow CA\_GEN\_SA(Param, \tau, Constraints)$
3: $T_{pass}, T_{fail} \leftarrow execute(T)$
4: **for each** $t_{fail} \in T_{fail}$ **do**
5: $mfs \leftarrow OFOT(t_{fail})$
6: $MFS.append(mfs)$
7: **end for**
8: **return** MFS

Algorithm 4 The overall procedure of augmented SCT

Input: $Param$ ▷ the parameter values of the SUT
τ ▷ the strength of the covering array
$Constraints$ ▷ The constraints of SUT
Output: MFS ▷ The MFS of SUT
1: $MFS \leftarrow \emptyset$
2: $T \leftarrow CA\_GEN\_SA(Param, \tau, Constraints)$
3: $T_{pass}, T_{fail} \leftarrow execute(T)$
4: **for each** $t_{fail} \in T_{fail}$ **do**
5: $t_{mutated} \leftarrow t_{fail}$
6: **for each** $s \in MFS$ **do**
7: **if** $s \in t_{mutated}$ **then**
8: $t_{mutated} \leftarrow remove(t_{mutated}, s)$
9: **end if**
10: **if** $t_{fail} == t_{mutated}$ **then**
11: $mfs \leftarrow OFOT(t_{fail})$
12: $MFS.append(mfs)$
13: **else**
14: **if** $execute(t_{mutated})$ == FAIL **then**
15: $mfs \leftarrow OFOT(t_{mutated})$
16: $MFS.append(mfs)$
17: **end if**
18: **end if**
19: **end for**
20: **end for**
21: **return** MFS

each failing test case (line 6), the augmented SCT first needs to check whether there exists any existing MFS contained in it (line 6 - 7). If so, the augmented SCT needs to remove the existing MFS in it (line 8) by mutating the corresponding parameter values of the test case to any values other than the ones contained in the MFS. Note that if we have removed some MFS in the original failing test case (line 14), we need to execute the newly generated test case $t_{mutated}$ to see if it fails again (line 14). If it fails, which means that $t_{mutated}$ contained some MFS other than the previously identified MFS, the augmented SCT needs to take OFOT to identify the MFS in $t_{mutated}$. On the other hand, if we did not find any previously identified schema (line 10), the augmented SCT just needs to directly take OFOT to identify the MFS in the original failing test case. At last, the same as SCT, the augmented SCT needs to return all the identified MFS (line 21).

A.3 the algorithm of ICT

Algorithm 5 The overall procedure of ICT

Input: $Param$ ▷ the parameter values of the SUT
τ ▷ the strength of the covering array
$Cons$ ▷ The constraints of SUT
$CheckMAX$ ▷ The strength of checking mechanism
Output: MFS ▷ The MFS of SUT
1: $MFS \leftarrow \emptyset$ ▷ the identified MFS returned by this algorithm
2: $\Omega \leftarrow Valid\_\tau\_Schemas(Param, \tau, Cons)$ ▷ the uncovered schemas
3: $S_{MFS} \leftarrow \emptyset$ ▷ already identified MFS
4: **while** Ω is not empty **do**
5: $test \leftarrow Greedy\_Gen(\Omega, Cons, S_{MFS})$
6: **if** $execute(test)$ == PASS **then**
7: $\Omega \leftarrow Update(\Omega, test, \tau)$
8: **else** ▷ start OFOT, and checking process
9: $S_{mfs\_candi} \leftarrow \emptyset$
10: $T_{history} \leftarrow \emptyset$
11: **while** true **do**
12: $T_{for\_MFS} \leftarrow \emptyset$
13: **for each** $\Delta \in test$ **do**
14: $t_{\Delta} \leftarrow Mutate(\Delta, \Omega, S_{MFS}, Cons, T_{history})$
15: $T_{for\_MFS}.append(t_{\Delta})$
16: **if** $execute(t_{for\_MFS})$ == PASS **then**
17: $\Omega \leftarrow Update(\Omega, t_{\Delta}, \tau)$
18: **end if**
19: **end for**
20: $T_{history}.append(T_{for\_MFS})$
21: $S_{mfs\_candi} \leftarrow OFOT(T_{for\_MFS})$
22: $isRealMFS \leftarrow true$
23: **for** $i = 0; i <= CheckMAX; i++$ **do**
24: $t_{check} \leftarrow Gen(S_{mfs\_candi}, \Omega, S_{MFS}, Cons, T_{history})$
25: **if** $execute(t_{check})$ == PASS **then**
26: $\Omega \leftarrow Update(\Omega, t_{check}, \tau)$
27: $isRealMFS \leftarrow false$
28: break
29: **end if**
30: **end for**
31: **if** $isRealMFS == true$ **then**
32: break
33: **end if**
34: **end while**
35: $S_{current} \leftarrow S_{mfs\_candi}$
36: $\Omega \leftarrow ChangingCoveage(\Omega, S_{current}, S_{MFS})$
37: $S_{MFS}.append(S_{current})$
38: **end if**
39: **end while**
40: $MFS \leftarrow S_{MFS}$
41: **return** MFS

The inputs of Algorithm 5 contained one new parameter, i.e., $CheckMAX$, which is used to set the checking strength (number of test cases generated in checking mechanism).

This algorithm consists of two main loops. The outer loop (line 4 - 39) focuses on checking the un-covered schemas (line 4), and if it is not empty, *ict* needs to generate test cases (one test at a time) to cover them (line 5). Our

generation method for *ict* in this paper is AETG [8]. After generating the test case, *ict* needs to execute it (line 6) and if it passes, *ict* will update the un-covered schemas by eliminating the τ-degree schemas in it (line 6 - 7). Otherwise, *ict* will start the inner loop, i.e., the MFS identification stage (line 11 - 34).

There are two variables used in this inner loop. The first one is S_{mfs_candi} (line 9), which records the candidate MFS identified in each iteration of this loop. The other one is $T_{history}$ (line 10), which is used to record the test cases generated in each iteration of this MFS identification stage, such that it will not generate the same test cases as generated before.

In this inner loop, it first uses OFOT to identify a candidate MFS (line 12 - 21). Different from the original OFOT algorithm, for each test case t_Δ, *ict* needs to consider the following facts: 1) cover as more un-covered schemas Ω as possible, 2)do not contain existing identified MFS S_{MFS}, and constraints, 3) do not generate the test cases generated in the previous iterations (line 14). It is noted that in this paper, we use the same greedy method as used in AETG to generate such test case. Specifically, for the parameter value that is needed to select, *ict* selects the parameter value has the most un-covered schemas that contain this parameter value. Additionally, we use SAT solver to ensure that the selected parameter value will not introduce any constraint, any MFS, nor any test case that have already generated. After t_Δ is generated, *ict* will execute it (line 16), and if it passes, *ict* will update the un-covered schemas set (line 17). *ict* then identifies the candidate MFS S_{mfs_candi} according to the corresponding test cases generated by OFOT (line 21).

The second part of this inner loop is to check the S_{mfs_candi} to be real MFS or not (line 23- 33). Specifically, for each iteration of this checking mechanism (line 23), *ict* additionally generates one test case t_{check} (line 24). t_{check} must satisfy the following conditions: it should 1) contain the candidate identified MFS S_{mfs_candi}, 2)cover as more un-covered schemas Ω as possible, 3)do not contain existing identified MFS S_{MFS}, and constraints, 4) do not generate the test cases generated in previous iteration. Note that in this paper, t_{check} is generated the same way as we generate t_Δ. After t_{check} is generated, *ict* executes it and if it passes (line 25), *ict* will update the un-covered schemas set (line 26). Also, the pass of t_{check} indicates that S_{mfs_candi} is not the real MFS (line 27), and hence, *ict* will jump out the checking mechanism (line 28), and continue to re-identify the MFS. Otherwise, *ict* will regard S_{mfs_candi} as the real MFS after the checking mechanism (line 31), and *ict* will jump out the inner loop of MFS identification (line 32) to report the MFS it identifies (line 35).

At last, *ict* will update the uncovered schemas (line 36) by removing the identified MFS, and some other schemas that are related to it (super-schemas, implicated constraints). This algorithm repeats until there are no uncovered schemas, and it will return all the identified MFS (line 40 - 41).

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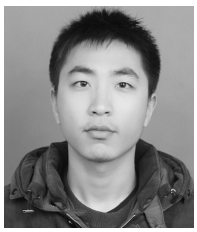

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