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

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

Abstract—Combinatorial testing(CT) seeks to detect potential faults caused by various interactions of factors that can influence the software systems. When applying CT, it is a common practice to first generate a set of test cases to cover each possible interaction and then to identify the failure-inducing interaction after a failure is detected. Although this conventional procedure is simple and forthright, we conjecture that it is not the ideal choice in practice. This is because 1) testers desire to identify the root cause of failures before all the needed test cases are generated and executed 2) the early identified failure-inducing interactions can guide the remaining test case generation, such 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.

- *Xintao Niu and Changhai Nie are with the State Key Laboratory for Novel Software Technology, Nanjing University, China, 210023. E-mail: niuxintao@gmail.com, changhainie@nju.edu.cn*
- *Hareton Leung is with Department of computing, Hong Kong Polytechnic University, Kowloon, Hong Kong. E-mail: hareton.leung@polyu.edu.hk*
- *Jeff Y. Lei is with Department of Computer Science and Engineering, The University of Texas at Arlington, Arlington, Texas. E-mail: ylei@cse.uta.edu*
- *Xiaoyin Wang is with Department of Computer Science, University of Texas at San Antonio. E-mail: Xiaoyin.Wang@utsa.edu*
- *JiaXi Xu and Yan Wang are with School of Information Engineering, Nanjing Xiaozhuang University. E-mail: xujiaxi@njxzc.edu.cn, wangyan@njxzc.edu.cn*

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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 between 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 fulfil 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 instead of dividing the generation and identification into two independent stages, it integrates these two stages together. 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.

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.

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 perform a series of comparisons with traditional CT and Feedback-driven CT. The result of the empirical studies are discussed.

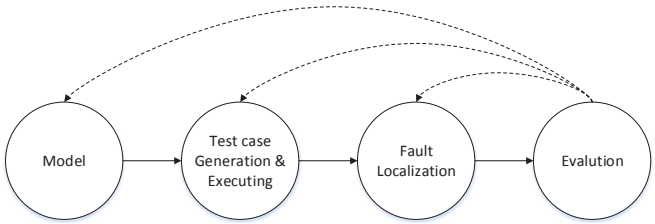

Fig. 1. The life cycle of CT

The rest of the paper is organised as follows: Section 2 presents the preliminary background of CT. Section 3 presents an motivating example. Section 4 describes our new framework and a simple case study is also given. Section 4.5 gives the limitation of our approach as well as some corresponding measures to handle it. 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. Note that failures discussed are assumed to be deterministic in this paper. This assumption is a common assumption of CT [7], [8], [9]. It indicates that the outcome of executing a test case is reproducible and will not be affected by some random events. Some approaches have already proposed measures to handle this problem [10], [11].

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 design 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 is regard 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 [12]:

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 [13], [14], [15].

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 optimising the coverage. If the coverage is finally satisfied, it will reduce the size of the set to see if fewer test cases can still fulfil the coverage. Otherwise, it will increase the size of test set to cover all the schemas [16], [17].

3) IPO-like style: This strategy differentiates from the previous two strategies in that it does not firstly generate complete test cases [18]. Instead, it first focuses on assigning values to some part of the factors or parameters to cover the schemas that 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 get a complete test case such 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 comparing 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 [19], [20], [21], 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 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 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, and as other mutating process all failed, which means no other failure-inducing factors were 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

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

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 [9], which is impossible in practice. Hence, all the existing MFS identification approaches, as well as the approach we will proposed in this paper, need additional assumptions or just identify the likely failure-inducing interactions. For example, approach proposed in [7] needs the *safe value* assumption, i.e., it assumes that the additional test cases do not introduce new MFS. And [8] just gives a rank of possible suspicious MFS.

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 [22], [23], [24] (HSQLDB works normally under some proper configurations, but crashes or throws exceptions under some other configurations).

Considering the large configuration space of HSQLDB, we firstly 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 successively 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 $parameterisedSQL$ 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 star).

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 following:

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

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	Fail
	t_7	2	**0**	1	1	Pass
	t_8	2	1	0	0	Pass
	t_9	2	2	0	0	Fail
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, -, -)**				

3.1 Redundant test cases

The first shortcoming of SCT is that it may generate redundant test cases, such that some of them do not cover as many uncovered schemas as possible. As a consequent, 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 word, if we firstly 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 can not handle multiple MFS that have overlapping parts [7], or consume too many additionally generated test cases [9], [25]. 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

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 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 (2)it is identified as MFS or faulty schema. Apparently, this criteria can not be satisfied with traditional covering array alone. 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 do 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.

4 Interleaving Approach

Considering these deficiencies of traditional sequential CT, 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 cooperated 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.

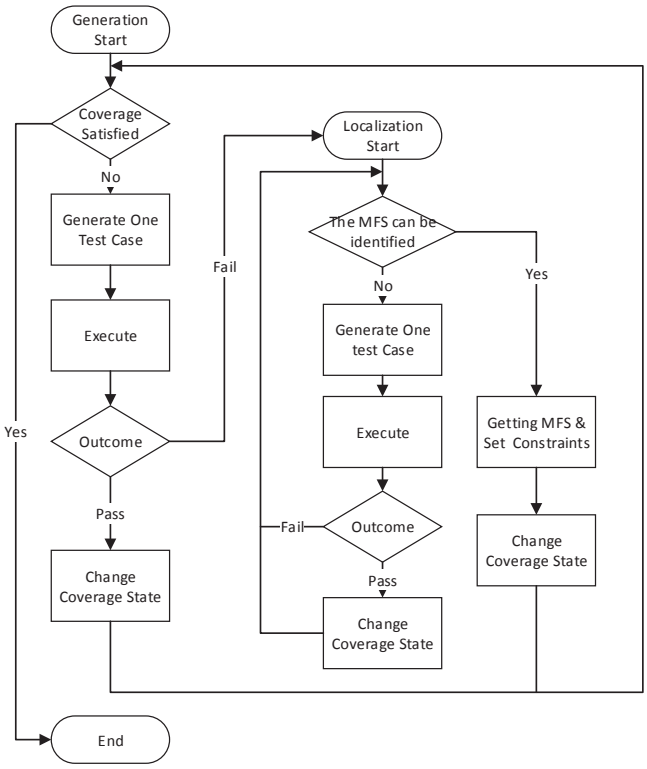

Fig. 2. The Interleaving Framework

In other word, the ultimate goal of this framework is to better support MFS identification and test case generation, such 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 pass (executed normally, i.e., does not triggered an exception, violate the expected oracle or the like) or 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 **implicit forbidden** schemas, which was first introduced in [26]. This type of schemas are 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 implicit forbidden schema. This is because for any test case that contain 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 firstly analysed the MFS 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 afterwards, 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 difference 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 traditional 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).

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

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

Algorithm 1 Changing coverage after identification of MFS

Input: $\mathcal{S}_{MFS}$ ▷ already identified MFS
Ω ▷ the schemas that are still uncovered
$\mathcal{T}_{all}$ ▷ all the possible 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 ∈ S_MFS do
2:     if s is t-degree schema then
3:         Ω ← Ω\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:             Ω ← Ω\s_p
8:         end if
9:     end for
10: end for
11: for each s ∈ Ω do
12:     if ∄t ∈ (T_all − T_MFS), s.t., t.contain(s) then
13:         Ω ← Ω\s
14:     end if
15: end for
```

In this algorithm, we firstly check each MFS (line 1) to see if it is a t-degree schema (line 2). We will set those t-degree MFS as covered and remove them from the uncovered schema set Ω (line 3). This is the first type of schemas – *themselves*. For each t-degree super-schema of these MFS, it will also be removed from the uncovered schema set (line 5 - 9), as they are the second type of schemas – *super-schemas*. The last type, i.e., *implicit forbidden schemas*, is the toughest one. To remove them, we need to search through each potential schema in the uncovered schema set (line 11), and check if it is the implicit 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 implicit 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, a SAT solver will be utilized to do this checking process.

4.2.1 MFS identification approach mutated

This interleaving framework can reduce the likelihood of having multiple MFS in a single test case, which in turn is due to the way the approach operates, i.e., one failure at a time. However, it still does not guarantee to completely forbid the appearance of multiple MFS in one single test case, which has a significant impact on the MFS identification–OFOT, as we discussed in Section 3.2. Considering this, we need to augment the original OFOT approach, to alleviate the negative influence when facing the test case with multiple MFS.

Inspired by the interim method proposed by Zhang [7], we find the method *FIC*– a mutated version of OFOT, can work well under the multiple MFS condition. The mechanism of FIC is very similar to OFOT. Specifically, when identifying the MFS in a failing test case, it also mutates one factor at a time to generate one additional test case. The only difference is that it will not always rollback to the original value it has mutated when it goes on mutating other values (only when a passing test case appears, it will rollback to the original value). This operation will break multiple MFS in one test case and finally there remains only one MFS to identify. For example, assume a SUT has 4 parameters and each one has 2 values, the MFS are (0, -, -, -) and (- ,-, 1 ,1). Then Table 5 shows the process of approaches OFOT and FIC for identifying the MFS of failing test case (0, 0, 1 1)

TABLE 5
The difference between FIC and OFOT

OFOT						***FIC***					
t_1	0	0	1	1	Fail	t'_1	0	0	1	1	Fail
t_2	1	0	1	1	Fail	t'_2	1	0	1	1	Fail
t_3	0	1	1	1	Fail	t'_3	1	1	1	1	Fail
t_4	0	0	0	1	Fail	t'_4	1	1	***0***	1	Pass
t_5	0	0	1	0	Fail	t'_5	1	1	***1***	***0***	Pass
MFS: $(-,-,-,-)$						**MFS:** $(-,-,1,1)$					

In Table 5, the left part represents OFOT. We can learn that no matter which parameter we mutate, the additional test cases ($t_2 - t_5$) will either contain MFS (0, -, -, -) or (-, -, 1, 1). While for FIC, as it does not rollback to the original value when the additional test case fails, hence, the mutated value for t'_2 and t'_3 will kept in the latter iterations. As a result, the first MFS (0, -, -, -) will be broken and will not appear in the later generated test cases. When the additional test case passes (t'_4 and t'_5), the process is completely the same as OFOT. At last, FIC will find the MFS (-, -, 1 , 1), as only when changing of last two parameter values, additional test cases will pass. Note that this mechanism will not always work. For example, if additional test case, e.g., t'_4, import new MFS, e.g., (1, -, 0, -), then we cannot get the correct MFS. The newly introduced MFS problem has already been discussed in our previous paper [9], in which we find that more test cases need to be generated to alleviate the impacts caused by the newly introduced MFS. This point is, however, beyond the scope of this paper. What's more, as we found in the our empirical studies, the mutated OFOT approach, i.e., FIC, is good enough to handle the multiple MFS in one test case than the original OFOT.

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 [27]. 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 forbidden those invalid schemas appear in the generated test cases [22], [27], [28], [29], [30]. 2) dynamic method, that is, it does not initially know which are constraints, but identify them as MFS and forbidden them in the latter iteration [5]. We adapt the second method for constraints handling, as it can directly applied into our framework.

Specifically, when we execute invalid test cases which cannot be executed or even complied, we will identify these invalid schemas which trigger this problem. In other word, 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 also some possible implicit illegal schemas to appear in the latter generation (through the same way for those identified MFS).

In a more detailed view, those forbidden schemas are formulated into clauses, as introduced in [27]. 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 [31] to obtain a solution (that is, a test case that avoid these forbidden schemas). It is noted that, besides these forbidden schemas, there has 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 [27], [28].

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 such that the overall cost is reduced***:
   Two facts of our framework support this improvement: (1) The schemas appeared in the passing test cases generated for MFS identification are counted towards the overall coverage, so that the test case generation process converges faster, which results in generating a smaller number of test cases. (2) The forbidden of identified MFS. As a result, test cases which contain these MFS will not appear, as well as those additionally generated test cases used to re-identify these MFS.
2) ***The appearance of multiple MFS in the same test case is limited, improving the effectiveness of MFS identification***
   This is mainly because we forbid the appearance of MFS that has been identified. Consequently, following our approach, the number of remaining MFS decreases one by one. Correspondingly, the probability that multiple MFS appear in the same test case will also decrease. Since multiple MFS has a negative effect on MFS identification as discussed in Section 3, the reduction of the appearance of multiple MFS in the same test case obviously improve the effectiveness of MFS identification.
3) ***The Masking effect is reduced, 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.

4.4 Demonstration on An Example

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

TABLE 6
Interleaving CT case study

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

This table consists of two main columns, in which the left column indicates the generation part while the right indicates the identification process. We can find that, after identifying the MFS (-, 0, -, -) for t_1, the following test cases (t_6 to t_{15}) 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., (1, 1, -, -), (1, -, 0, -), (1, -, -, 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 contain one MFS as expected, and we easily identified it (-, -,

0, 1) with four additionally generated test cases. 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 case are 8 less than that of the traditional sequential CT approach in Table 4, and the new approach identified the expected MFS (-, -, 0, 1) which SCT fails to identify.

4.5 Discussion

To forbid identified MFS in the later generated test cases is efficient for CT, as it will reduce many unnecessary test cases. On the other hand, our framework has strict requirements in 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.

For example, suppose we incorrectly regard (-, -, 0, -) as MFS of the failing test case t_1 in Table 6, then we will never generate test cases containing the real MFS (-, -, 0, 1) (t_8 in Table 6, for example). Hence, (-, -, 0, 1) will never be detected and identified. Additionally, the uncovered 2-degree schemas like (1, -, 0, -) (-, 2, 0, -), (-, 1, 0, -), etc, will never be covered in the later generated test cases.

To exactly identify the correct MFS in one failing test case, if possible, however, is not practical due to the cost of testing [6], [19]. 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 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], [7], [8], [9], [19], [20], [32].

Based on the insight that incorrect identification of MFS is inevitable, our approach surely suffer from the two problems discussed previously, but the following measures can help to alleviate such impacts:

1) **Combining MFS identification approaches**: Utilizing different approaches is appealing for our framework, as it can improve the robustness of the MFS identification and hence render a more reliable result. Specifically, when a failure is triggered by a test case, instead of only using OFOT, we apply multiple MFS identification approaches (FIC_BS [7], classification tree [10], for example) to identify the MFS. Subsequently, we filter out obtained schemas unless at least two identification approaches produce them as MFS. This simple voting mechanism can improve both precision and robustness of identified MFS. Particularly, the incorrectly identified MFS can be eliminated if it is obtained by only one identification approach, and MFS that are omitted by one approach can be identified by other approaches.

2) **Tolerating mechanism (Weak forbidden)**: Unlike our basic *ICT* framework that rigorously forbids the identified MFS, we can permit some identified MFS to appear in the later generated test cases incidentally. This extension can make ICT tolerant of incorrectly identifying MFS to some extent, as it increases the chance that the covering array checks them again and re-identify whether they are MFS or not. When to let the identified MFS re-appear in a test case is important, as it affects the efficiency of our framework (If they re-appear too many times, many test cases will fail and MFS identification will repeat again and again, which is inefficient). It is worthwhile to obtain a balance between the appearance of existing MFS and the cost of overall testing.

3) **More rigorous validation** This approach needs cooperation from developers of the SUT. Specifically, when a MFS is identified, not only should we send it to developers of the SUT, but also we need to get the feedback from them to see whether this MFS is the root cause of failure or not. Although this process may be time-consuming and delay the testing for the remaining bugs, it is the most effective way to determine the correct MFS.

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

Q4: What is the sensibility of our approach to different number of MFS and different number of options in SUT?

5.1 Subject programs

The five subject programs used in our experiments are listed in Table 7. 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).

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

TABLE 7
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

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 ranged 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 are caused by the interaction of configuration options. Then for each such bug, we derive 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 an 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 7, 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 8.

TABLE 8
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(2)
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 can take on 3 values, and only one parameter that can take 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 in the experiment is AETG [13], 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 [27], [28] 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 [14], or other MFS identification techniques [7], [9], 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 focus on the overall CT process.

5.2.1 Study setup

For each software except *Tcas*, a test case is determined to be passing if it ran without any exceptions; otherwise it is regarded as failing. For *Tcas*, as the fault is injected, we determine the result of a test case by separately running it with the original correct version and the mutation version. The test case will be labeled as passing if their results are the same; otherwise, it is deemed as failing.

In this experiment, we focus 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. So to avoid the biases of randomness, we conduct each experiment 30 times and then evaluate the results. (Note that the remaining case studies are also based on 30 repeated experiments.) For each run of the experiment, we separately applied traditional 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 are generated in the CT generation and MFS identification, respectively, are 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 comparing 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 9 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 total number of test cases generated by our approach are far less than that of the traditional approach. In fact, except for subject *Tcas*, our approach reduced about dozens of test cases for 2-way coverage, and hundreds of test cases for 3-way and 4-way coverage. For *Tcas*, however, we find that both approaches rarely trigger errors. This is because most of the MFS of TCAS are of high degree (t $>$ 6), and the covering arrays (t = 2, 3, 4) rarely detect any of them. As listed in Table 10, the recall of both approaches are very low (both for 2, 3, 4 wise covering array), indicating that the MFS is rarely detected and identified. As a result, both *ict* and *sct* will not start the MFS identification process, and hence the overall process will be transferred to be traditional covering array generation.

The gap of total number of test cases is mainly due to the difference in the number of test cases generated in *MFS identification* activity. In fact, their results in the *CT generation* are almost the same. Even for $4 - way$ coverage criteria which may need thousands test cases, the gap between them are no more than 10.

For *MFS identification* activity, the interleaving approach only consumed a relatively small amount of test cases when compared to the sequential approach. What's more, the interleaving approach obtained almost the same results under the 2-way, 3-way, and 4-way coverage (see the cells in bold). This is as expected, as the MFS identification only happens after a test case fails in our interleaving approach. After the identification process, the identified MFS will be set as forbidden schemas for the later generated test cases. As a result, each MFS only needs to be identified once, no matter what the coverage is and how many test cases needed to be generated.

However, this is not the case for the sequential approach *sct*. As discussed before, the sequential approach does not identify the MFS at early iteration, so that these MFS can appear in latter test cases. As a result, it needs many more test cases to identify the same MFS , which is a huge waste. Even worse, the more test cases generated in *CT generation* activity, the more test cases are needed in *MFS identification* activity (See the Column 'Iden' of sequential approach under 2-way, 3-way and 4-way coverage). This is because the possibility that failures are triggered is increased when there are more test cases without forbidding the appearance of these MFS.

With regard to the quality of the identified MFS, the comparison of the two approaches are listed in Table 10. Based on this table, we find that there is no apparent gap between them. For example, there are 7 cases under which our approach performed better than the traditional one (marked in bold). Among these cases, the maximal gap is just 0.37 (4-way for Gcc), and the average gap is around 0.1, which is trivial.

The reason of the similarity between the quality of these two approaches is that both of them have advantages and disadvantages. Specifically, our approach *ict* can reduce the impacts when a test case contains multiple MFS. As discussed in section 3.2, multiple MFS in a test case can reduce the accuracy of the MFS identifying algorithms [9]. As a result, our approach can improve the quality of the identified schemas (details are given in the next study). But as a side-effect, if the schemas identified at the early iteration of our approach are not correct, they will significantly impact the following iteration. This is because we will compute the coverage and forbid schemas based on previously identified MFS. It was the other way around for *sct*. It suffers when a test case contains multiple MFS, but correspondingly, previous identified MFS has little influence on the traditional approach *sct*. Note that in the case studies, we do not apply the measures proposed in Section 4.5, which we believe can improve the quality of the MFS identification.

Another interesting observation with regard to the MFS identification is that higher t-wise strengths are not always resulting an improved precision (For example, the precision of *ict* and *sct* with the 2-way covering array for Hsqldb are 0.9 and 0.7, respectively; while the precision are 0.72 and 0.5 with 3-way covering array). 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. This is because a t-wise covering array can detect all the failures caused by the MFS of t-degree, or less than t-degree. Then, if a MFS is detected, *ict* and *sct* can identify them as expected. It is surely that a higher-wise can also detect those low degree MFS. 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).

TABLE 9
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	15.3	**44.1**	59.2	41.6	**60.8**	102.3	86.9	**46.2**	133.1
	sct	13.8	104.1	116.6	38.3	252.7	289.3	91.3	567.4	653.2
Hsqldb	ict	14.9	**18.6**	33.5	44.0	**30.5**	74.5	116.8	**34.7**	151.5
	sct	15.8	124.7	139.7	47.4	366.4	412.0	121.8	870.4	989.8
Gcc	ict	14.6	24.8	39.3	49.0	**30.2**	79.2	99.1	**43.9**	142.8
	sct	15.0	19.7	34.7	51.0	64.1	114.8	101.9	124.2	224.7
Jflex	ict	15.8	**14.0**	29.8	49.6	**14.0**	63.6	131.8	**14.0**	145.8
	sct	16.2	33.6	49.8	50.8	148.2	199.0	133.8	426.4	559.8
Tcas	ict	108.9	0.0	108.9	417.5	1.2	418.7	1545.7	**5.9**	1551.6
	sct	109.0	0.0	109.0	418.0	0.0	418.0	1545.0	7.2	1552.2

TABLE 10
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	0.64	0.6	0.6	0.8	0.73	0.76	0.88	0.87	**0.87**
	sct	0.71	0.77	0.73	0.75	1.0	0.86	0.75	1.0	0.86
Hsqldb	ict	0.9	0.47	**0.6**	0.72	0.67	**0.69**	0.77	0.8	**0.79**
	sct	0.7	0.43	0.53	0.5	0.5	0.5	0.5	0.67	0.57
Gcc	ict	0.59	0.38	**0.45**	0.6	0.5	**0.54**	0.75	0.8	**0.77**
	sct	0.35	0.17	0.23	0.34	0.42	0.37	0.33	0.5	0.4
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	0.0	0.0	0.0
	sct	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Additionally, Table 11 shows the milliseconds consumed by the two approaches on average. The experiment is conducted on Machine HP ProDesk 600 G1 TWR (Intel Core i5, 3.3Hz, 16GB memory). Based on this table, it is obviously that *ict* costed more time than *sct*. This is because *ict* needs to handle the SAT problem (for forbidding the appearance of MFS and constraints), which needs additional computing resources than *sct*. Considering the long test case execution time of large software projects, however, this extra test case generation time of *ict* is trivial in most cases.

TABLE 11
Time consumes (millisecond)

Subject	Method	2-way	3-way	4-way
Tomcat	ict	133.3	663.8	1642.7
	sct	5.8	40.6	200.1
Hsqldb	ict	47.6	403.2	2190.9
	sct	10.9	106.4	732.3
Gcc	ict	47.8	242.1	1307.5
	sct	7.4	52.9	227.9
Jflex	ict	74.8	541.8	3290.6
	sct	82.0	327.6	2395.4
Tcas	ict	97.8	1378.0	23406.1
	sct	139.6	1709.6	22614.0

In summary, the answer to **Q1** is: our approach needs much fewer test cases than the traditional sequential CT approach, and there is no decline in the quality of the identified MFS when comparing with the traditional approach, but the traditional sequential CT costs less time than our approach.

5.3 Alleviation of the three problems

Section 3 shows three problems that impact the performance of traditional 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 impacts.

5.3.1 Study setup

We design three metrics for each of the three problems. First, to measure the *redundant test case generation*, we gather the number of times that each schema is covered. This metric directly indicates the redundance of generated test cases, as 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 as 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 exist 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* is simple, we just directly search for each generated test case and examine if it contains more than one MFS.

Third, we use the *tested-t-way* coverage criteria [5] to measure the masking effects. Specifically, we re-compute the coverage of the test cases generated by ICT and SCT by counting all the *t*-degree schemas that is 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.

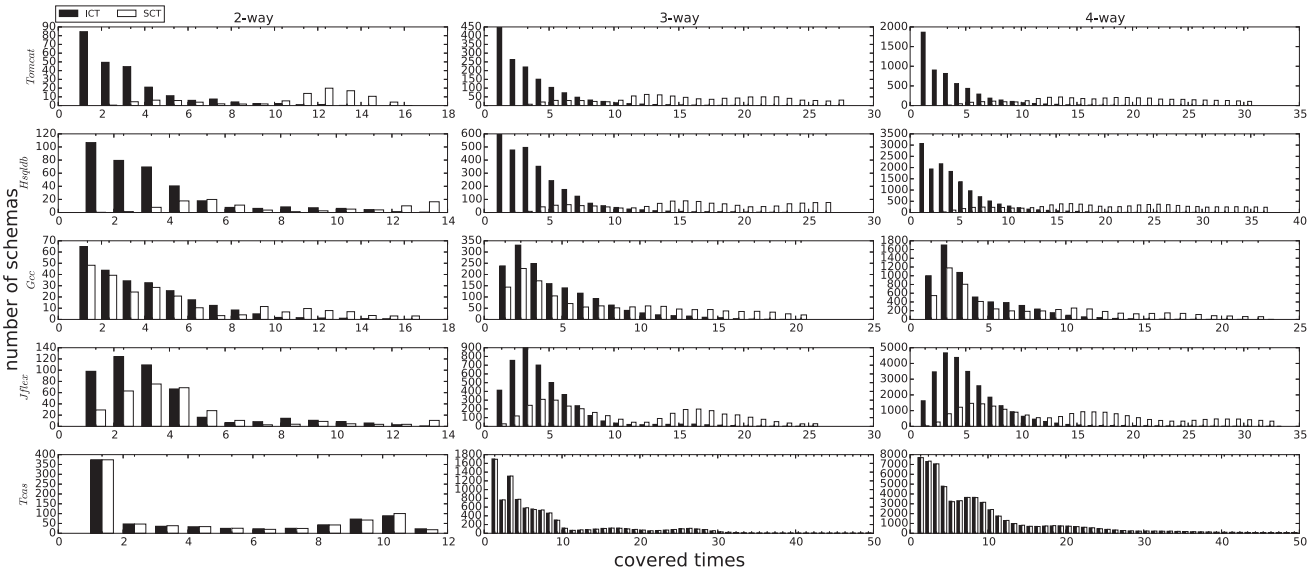

Fig. 3. The redundance of test cases

5.3.2 Result and discussion

1) **Redundant test cases**.

Our result is shown in Figure 3. This figure consists of nine 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, 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 2 indicates that *ICT* approach have 84.6 schemas in average which are covered twice and *SCT* have 4.4 schemas.

As discussed previously, the more schemas that 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) decrease with the increase of the covered times (x-axis). Most of the nine sub-figures indicate that *ict* performs better than *sct*. In fact. for *ict*, the bars decrease rapidly with the increase of x-axis, while for *sct*, the trend is more smooth. See subject tomcat with 2-way coverage for example, *ict* have about 84.6 schemas which are only covered once, about 49.5 schemas covered twice, less than 10 schemas with the covered times more than 6. For *sct*, however, for most covered times, it has about 10 schemas, which indicates a very low performance. The interesting exception is subject Tcas, on which *ict* and *sct* show 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 detect any of them. Under this condition, since both approaches rarely detected the MFS, the overall process will be transferred to be traditional covering array generation (the MFS identification process is omitted).

This result shows that our two modifications of 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 12, which lists the number of test cases (on average for the repeated 30 experiments) that contain more than one MFS.

TABLE 12
Number of test cases that contain multiple MFS

Subject	Method	2-way	3-way	4-way
Tomcat	ict	0.6	0.0	0.0
	sct	1.1	4.7	10.9
Hsqldb	ict	0.0	0.0	0.0
	sct	0.6	1.6	4.5
Gcc	ict	0.8	0.6	0.7
	sct	0.7	2.0	3.3
Jflex	ict	0.0	0.0	0.0
	sct	0.0	0.0	0.0
Tcas	ict	0.0	0.0	0.0
	sct	0.0	0.0	0.0

From this table, one observation is that *ict* obtained a better result than *sct* at limiting the test cases which contain multiple MFS. For all the subjects except *Gcc*, *ict* nearly eliminated all the test cases which contain multiple MFS. Even if for *Gcc*, the test cases which contain multiple MFS are less than that of *sct*. For *sct*, however, the result is not as good as *ict*. In fact except subjects *Jflex* and *Tcas*, *sct* suffers from generating test cases which contain multiple MFS. This is why even though *sct* generate much more test cases than *ict*, it did not obtain a better MFS identification result than *ict*. Two exceptions are subjects *Jflex* and *Tcas*, on which both *ict* and *sct* did not generate test cases containing multiple MFS. The reason is that *Jflex* has only one MFS (see Table 8) 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 13. There are two parts in this table, in which the left part shows the *tested-t-way* coverage for each approach. Specifically, the number of *t*-degree (*t* = 2, 3, 4) schemas which are *tested* (in the passing test cases or identified as

TABLE 13
Masking effects results

Subjects	Method	Tested-t-way coverage			non-masked test cases		
		2-way	3-way	4-way	2-way	3-way	4-way
Tomcat	ict	224.0(94.92%)	1368.4(96.10%)	5467.8(97.64%)	**14.7**	**41.6**	**86.9**
	sct	228.6(96.86%)	1404.0(98.60%)	5551.2(99.13%)	12.7	33.6	80.4
Hsqldb	ict	**357.0(100.00%)**	**2737.3(99.83%)**	**14097.0(99.72%)**	14.9	44.0	116.8
	sct	350.9(98.29%)	2725.3(99.39%)	14068.2(99.52%)	15.2	45.8	117.3
Gcc	ict	251.4(99.76%)	1520.8(99.01%)	5959.3(98.53%)	13.8	48.4	98.4
	sct	251.6(99.84%)	1532.2(99.75%)	6014.9(99.45%)	14.3	49.0	98.6
Jflex	ict	473.0(100.00%)	4282.0(100.00%)	26532.0(100.00%)	15.8	49.6	131.8
	sct	473.0(100.00%)	4282.0(100.00%)	26532.0(100.00%)	16.2	50.8	133.8
Tcas	ict	837.0(100.00%)	9158.0(100.00%)	64696.0(100.00%)	108.9	417.5	**1545.7**
	sct	837.0(100.00%)	9158.0(100.00%)	64696.0(100.00%)	109.0	418.0	1545.0

faulty schemas) are gathered, as well as the percentage of the total *t*-degree schemas (in the parentheses followed). While the right part shows the number of test cases that ignores the masking effects (i.e., the test cases with no multiple MFS). 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 94.92% (2-way for Tomcat) and *sct* is 96.86% (2-way for Tomcat). This 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. Additionally, the number of test cases that ignores the masking effects accounts for a great proportion of the test cases in *CT generation*, indicating that both approaches do not suffer too mach from the masking effects.

Second, there is no apparent gap between *ict* and *sct* at restricting the masking effects. With respect to *tested-t-way* coverage, there are three cases (shown in bold) that *ict* are better than *sct*, six cases that they are equal (for subjects *Jflex* and *Tcas*) and remaining six cases that *sct* is better. With respect to the number of non-masked test cases, the gap between them is also trivial (no more than 10 test cases for all the 15 cases). As we discussed before, *ict* forbids the appearance of identified MFS and can improve the performance at handling masking effects. The results, however, do not show this advantage. The reasons are manifold. Specifically, for *ict*, while forbidding identified MFS in the later generated test cases can reduce masking effects, but the incorrectly identified MFS may make this effort in vain. That is, if the schemas identified by our framework is not the real MFS, then it will not contribute to the reduction on masking effects. This conclusion can also be manifested in Table 10, where the f-measure of ict is not always 1.0, indicating that the MFS identified is not always accurate. On the other hand, for *sct*, while it does not forbid any MFS in the test case generation stage, but it generates more test cases than *ict* (many of them are redundant and cover the same schemas several times). Hence, *sct* may obtain more chances to revise their MFS identification. That is, if it incorrectly identifies the MFS in one failing test case, it may obtain the correct MFS in the next failing test case, and this will improve the performance on reduction of masking effects.

Third, if there is only single MFS or MFS is not detected, the tested-t-way coverage is 100% for both *ict* and *sct*. This can be observed in subjects *Jflex* and *Tcas*, in which all the *t*-degree schemas are covered. For single MFS, as MFS identification is effective, all the other *t*-degree schemas can be determined as irrelevant to the failure. Consequently, the tested-t-way coverage is satisfied. For the case that MFS cannot be detected (MFS with high degrees), traditional *t*-way covering arrays are enough to obtain adequate testing, as all the test cases will pass if there is no MFS detected.

In summary, the answer to **Q2** is that our approach can alleviate the three problem discussed in Section 3, especially on reducing the redundance of test cases and limiting the test cases with multiple MFS. Additionally, both *ict* and *sct* have a good performance on reducing the masking effects.

5.4 Comparison with FDA-CIT

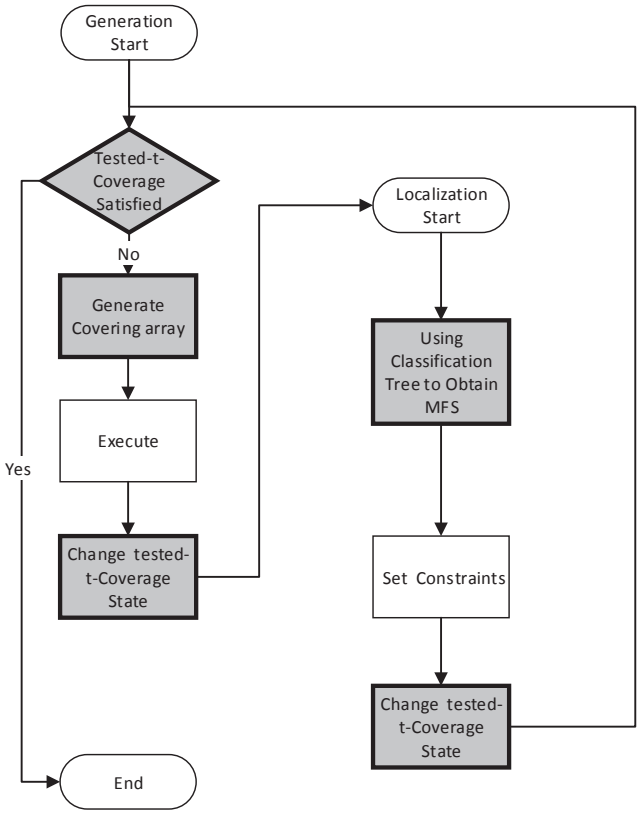

Fig. 4. The Framework of fda-cit

fda-cit [5] is a feedback framework that can augment the traditional covering array to iteratively identify the MFS, and can handle the masking effects. The overall process can be illustrated in Figure 4. Specifically, it will first generate a *t*-way covering array and execute all the test cases in it. After that it will utilize the classification tree method to identify the MFS. Then it will forbid the identified MFS to be appeared and compute the tested-t-way coverage. If the tested-t-way coverage is not satisfied, it will repeat the previous process, i.e., generating additional test cases and identifying MFS. Like our *ict* approach, FDA-CIT is also an adaptive approach which iteratively generates test cases and identifies the MFS. Besides these commonalities, there are several important differences between our approach and *fda-cit* (shaded in Figure 4):

First, the **granularity** of adaptation. Instead of handling one test case one time as *ict*, *fda-cit* tries to generate a batch of test cases at each iteration (A complete covering array will be generated at the first iteration, and more test cases will be supplemented to cover those *t*-degree schemas which are masked at latter 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 is a large number of failing tests, and a small size test suite, there is little information to exclude the particular MFS [7].

Third, the **coverage criteria** 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.

Next, we will design experiments to measure the performance of *fda-cit*.

5.4.1 Study setup

The design of this case study is similar to the previous two. For each subject in Table 7, we apply *fda-cit* to generate test cases and identify the MFS. After that, we gather 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 two metrics, i.e., covered times of schemas, and the t-tested-coverage. Note that in this study, we do not gather the test cases which contain multiple MFS, as the post-analysis classification tree method is not affected by this factor. The same as previous experiments, we will repeat each experiment 30 times for different coverages (2, 3, and 4 way), and then gather and analyse the average data.

5.4.2 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 14. 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 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* is better than *sct* at almost all cases. Combining the results of previous studies for *sct* and *ict*, we can conclude that *sct* is the most inefficient approach at test case generation. Second, for *ict* and *fda-cit*, there are ups and downs on both sides. In detail, *fda-cit* needs less test cases at lower coverage (mainly for the 2-way coverage), while *ict* performs better at higher coverage.

This result is reasonable. First, *fda-cit* does not need additional test cases to identify the MFS, which will reduce some cost when comparing 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 will 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 15. Same as previous metric, the comparison between fda-cit with *ict* and *sct* are 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 can hardly detect failures (with F-measure equal to 0), *ict* leads over *fda-cit* by about 10% to 50%, which is not trivial. The result is similar when comparing *sct* with *fda-cit*.

This result suggests that the classification tree approach, 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 [38]. 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* tend to be super-schema of the real MFS. Although this leads to the f-measure of MFS identification lower than that of *ict*, it does not have much negative influence on the masking effects reduction. This because to forbid the appearance of super-schema of real MFS will not reduce the number of schemas that is not MFS to be tested. As a result, the *tested-t-way* coverage is not changed (This coincides well with the experimental results).

TABLE 14
Number of test cases generated by *fda-cit*

	2-way	3-way	4-way
Tomcat	28.8(-30.4,-87.8)	65.2(-37.1,-224.1)	146.8(**13.7**,-506.4)
Hsqldb	27.6(-5.9,-112.1)	82.8(**8.3**,-329.2)	204.0(**52.5**,-785.8)
Gcc	22.0(-17.3,-12.7)	64.4(-14.8,-50.4)	127.2(-15.6,-97.5)
Jflex	20.2(-9.6,-29.6)	64.8(**1.2**,-134.2)	177.8(**32.0**,-382.0)
Tcas	109.4(**0.5**,**0.4**)	416.6(-2.1,-1.4)	1549.4(-2.2,-2.8)

TABLE 15
The F-measure of MFS identification for *fda-cit*

	2-way	3-way	4-way
Tomcat	0.27(-32.94%,-45.92%)	0.31(-44.89%,-54.60%)	0.33(-53.52%,-52.38%)
Hsqldb	0.42(-18.29%,-11.29%)	0.27(-42.08%,-23.13%)	0.31(-47.14%,-25.71%)
Gcc	0.08(-37.12%,-14.57%)	0.37(-16.82%,**0.03%**)	0.37(-39.39%,-2.51%)
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(0.00%,0.00%)

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 redundance between *ict* and *fda-cit* are similar, which is not severe when comparing with *sct*.

4)**Masking effects**. The result is listed in Table 16 and Table 17, of which the first shows the results of *tested-t-way* coverage and the second shows the number of test cases ignores the masking effects. For the two tables, 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 except subject Jflex (with single MFS) and Tcas (wit the high-degree MFS) which all three approaches work normally without masking effects, the schemas of other subjects do not get completely covered by the three approaches. Additionally, there do not exist apparent gaps between the three approaches. For example, *fda-cit* decreased about 5.71% and 7.61% at tested-2-way coverage than *ict* and *sct*, respectively, for the subject Tomcat, but also increased about 1.68% at tested-3-way coverage than *ict* for subject Tomcat, and is about 0.18% better than *sct* at tested-4-way coverage for subject Hsqldb. In fact, there are three cases (shown in bold) that *fda-cit* performed better than *ict*, and six cases that *fda-cit* did not. The gap between the three approaches for *tested-t-way* coverage is very trivial.

With regard to *the number of test cases which ignore the masking effects*, we find that for almost all the cases (except tested-3-way coverage of Tcas), *fda-cit* performs better than both *ict* and *sct*. This is because for approaches *ict* and *sct*, the proportion of test cases for identifying the MFS is not trivial. Considering there is little difference between the overall size of test cases generated by *fda-cit* and *ict*, it is easily to learn that the number of test cases generated for *CT generation* of *fda-cit* is larger than *ict* and *sct*. As a consequence, the number of test cases generated by *ict* that can be counted as ignoring the masking effects is smaller than that of *fda-cit*. In other words, if we take the test cases for identifying the MFS into account for *ict*, *the number of test cases which ignore the masking effects* of *ict* is actually similar to that of *fda-cit*.

Above all, this result suggests that our approach *ict* does reach the same level as *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 accurately is more important and should be the key focus in the future studies of masking effects.

To summarize, the answer to **Q3** is that when comparing with the adaptive CT approach *fda-cit*, our approach works as good as it, even at reduction of masking effects and making testing adequately which *fda-cit* focuses on addressing. Additionally, our approach supports a better MFS identification than *fda-cit*.

Note that one reason that *ict* performs better 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* is a better choice, as it does not need additional test cases for MFS identification and can handle the multiple test files, i.e., test case-aware condition [5].

5.5 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*.

5.5.1 Study setup

To vary parameters of interest in a controlled setting in this study, we use synthetic subjects instead of real programs

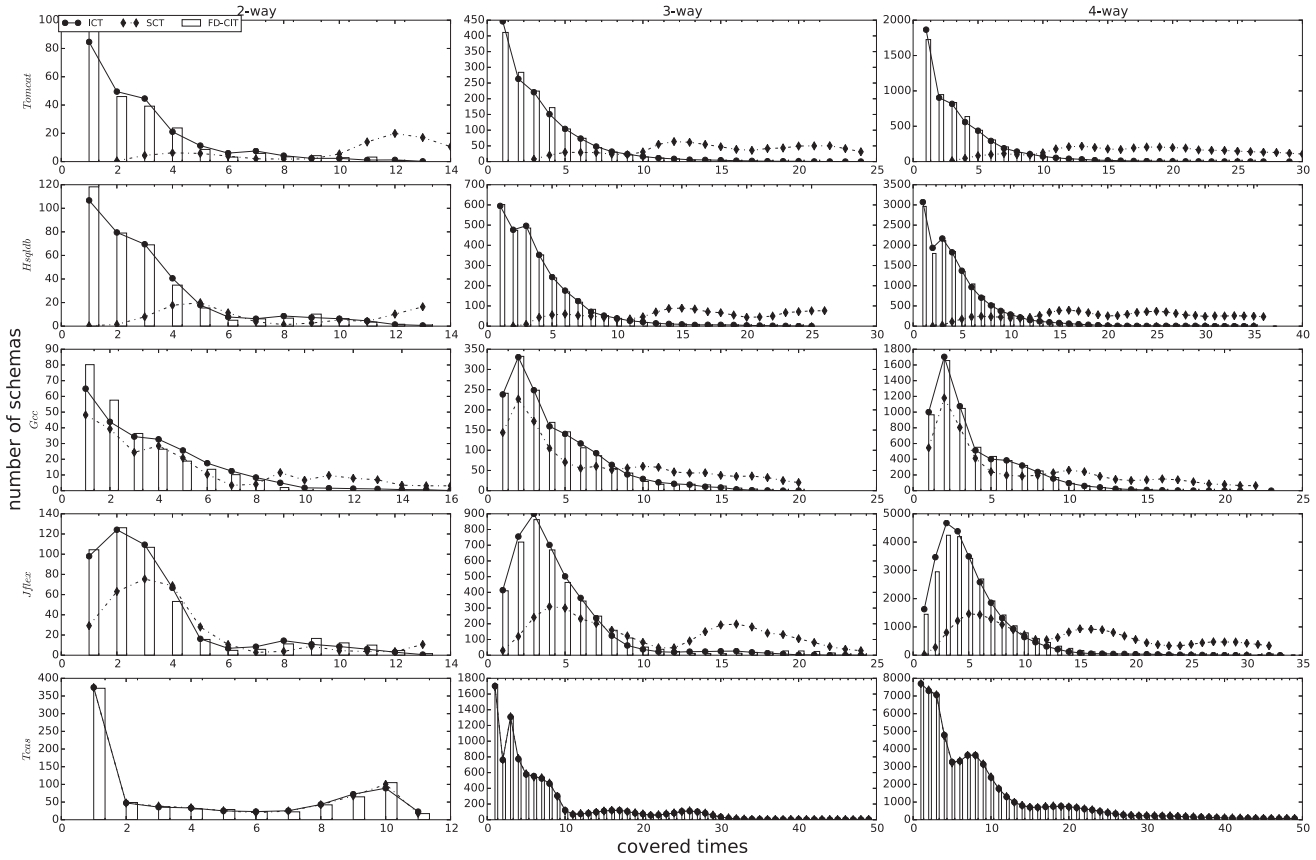

Fig. 5. The redundance of test cases generated by *fda-cit*

TABLE 16
The tested-t-way coverage for *fda-cit*

	2-way	3-way	4-way
Tomcat	211.2(-5.71%,-7.61%)	1391.8(**1.68%**,-0.87%)	5378.0(-1.64%,-3.12%)
Hsqldb	346.8(-2.86%,-1.17%)	2723.2(-0.52%,-0.08%)	14093.2(-0.03%,**0.18%**)
Gcc	251.0(-0.16%,-0.24%)	1531.2(**0.68%**,-0.07%)	6001.2(**0.70%**,-0.23%)
Jflex	473.0(0.00%,0.00%)	4282.0(0.00%,0.00%)	26532.0(0.00%,0.00%)
Tcas	837.0(0.00%,0.00%)	9158.0(0.00%,0.00%)	64696.0(0.00%,0.00%)

TABLE 17
Non-masked test cases for *fda-cit*

Tomcat	27.4(12.7,14.7)	60.4(18.8,26.8)	136.4(49.5,56.0)
Hsqldb	27.2(12.3,12.0)	81.8(37.8,36.0)	199.0(82.2,81.7)
Gcc	20.8(7.0,6.5)	61.6(13.2,12.6)	123.2(24.8,24.6)
Jflex	20.2(4.4,4.0)	64.8(15.2,14.0)	177.8(46.0,44.0)
Tcas	109.4(0.5,0.4)	416.6(**-0.9,-1.4**)	1549.4(3.7,4.4)

(which typically represent 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 use the subject with 8 parameters, and each parameter has 3 values, i.e., the inputs model is (3^8). Then we consider 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 will first inject the corresponding number of MFS into the synthetic subject, and then run all the three approaches on the subject. At last, the results (MFS identification quality and cost) of each approach for each run is collected and analysed.

The second study is to evaluate the performance of approaches under different number of options. Hence we use synthetic subjects with the following number of options (8, 9, 10, 12, 16, 20, 30, 40, 50, 60, 70, 80, 90, 100). Each option has 2 values, and each subject has only one 2-degree MFS. Then for each subject, we will apply the three approaches and compare their performance.

5.5.2 Number of MFS

The result for the sensitivity to the number of MFS is 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.

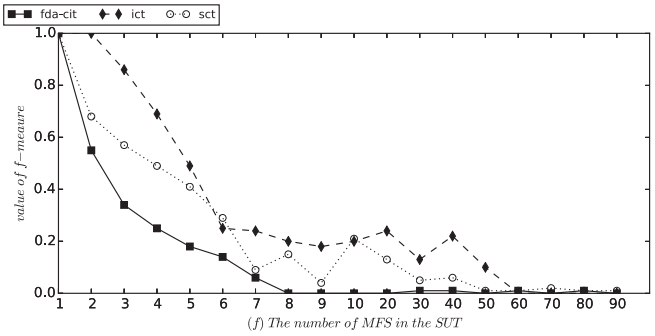

Fig. 6. F-measure for various number of MFS

One observation from Figure 6 is that, as the number of MFS increases, the f-measures of all three approaches decrease rapidly. In fact, when the number of MFS is greater than 50, the f-measures of all three approaches are near 0. This is mainly because when there are too many MFS, it is hard to get a passing test case, and hence, it is challenging to distinguish MFS from those schemas which are not related to the failures.

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

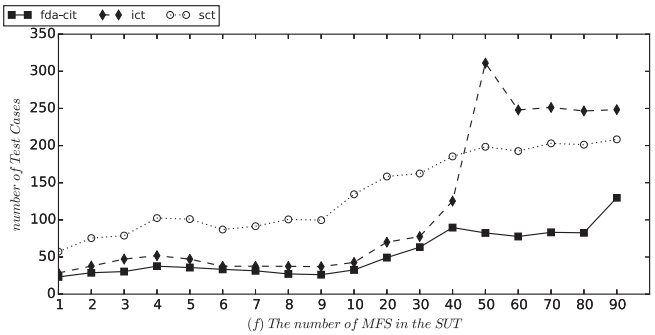

Fig. 7. Test Cases for various number of MFS

With regard to the cost, one observation is that with the increase of the number of MFS, all three approaches need more test cases to identify the MFS. The reason is obvious – a high number of MFS trigger more failing test cases, which needs more additional test cases for MFS identification. For *fda-cit*, even though it does not need additional test cases for MFS identification, a high number of MFS will lead to slower convergence. This is because it is harder to fulfil the *tested-t-way* coverage when there are too many failing test cases, and the slower convergence will surely result in more test cases generated.

Another interesting observation about the cost is that when the number of MFS is relatively small (less than 40), our approach *ict* shows a similar result with *fda-cit*, which is much smaller cost than that of *sct*. This result is consistent with what we had already obtained in Section 5.4. However, when the number of MFS is greater than 50, the cost of *ict* increases rapidly, which exceeds that of *sct* and *fda-cit*. The reason of this decline is that when MFS increases, almost all the test cases fail, and hence, the advantage that *ict* triggers fewer failing test cases will disappear. On the other hand, the more the failing test cases are generated, the harder *ict* can reach the coverage (because failing test cases do not contribute to the overall coverage). Hence, *ict* has to generate much more test cases than *sct* when the number of MFS reaches a vey large fraction.

Above all, with the increase of number of MFS in the SUT, the performance of all three approaches decreases, but *ict* still performs better than the other two approaches when the number of MFS is not extremely high, which is the common scenario in practice.

5.5.3 Number of options

The result for the sensitivity of number of options in the SUT is shown in Figure 8, which depicts the number of test cases needed with the increase of the number of options. Note that we do not show the MFS identification result because all three approaches obtain 1.0 of f-measures for all the cases. It shows that the number of options in the SUT does not influence the quality of MFS identification.

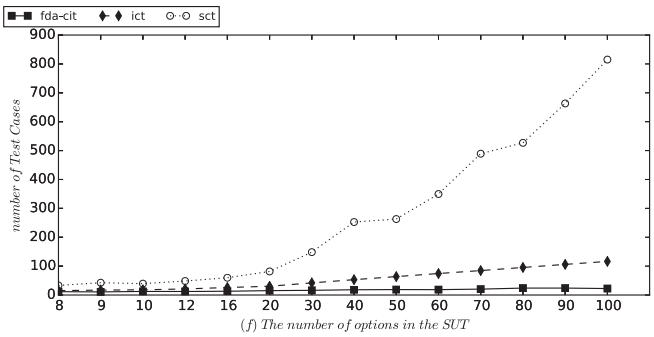

Fig. 8. Test Cases for various number of options

With regard to the number of test cases, there is a clear trend that *fda-cit* performs the best, of which the number of needed test cases grows slowly. This is mainly because it does not generate additional test cases for MFS identification. The second best is *ict*, as the number of test cases increases 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) [7], [9], [32]). The last one is *sct*, of which the number of test cases increases rapidly with the number of options.

In summary, the number of options in the SUT does not influence the quality of MFS identification; and although generating more test cases than *fda-cit*, *ict* is still a proper choice when considering the precision and recall in MFS identification among the three approaches.

5.6 Threats to validity

There are several 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 [13] as the test case generation strategy, and OFOT [6] as the MFS identification strategy. As different generation and identification algorithms may affect the performance 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 [39], especially on domains like configuration testing [10], [11], [40] and software inputs testing [13], [41], [42]. A recent survey [12] 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 [12]: 1) greedy methods [13], [14], [18], [43], which are very fast and effective, but may consume too many test cases. 2) mathematical methods [44], [45], [46], [47], 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 [16], [48], [49], [50], [51], [52] , which can generate very small size of test cases, but may cost much computation time and 4) random methods [53], [54], 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 [19] according to how the additional test cases are generated: *adaptive*–additional test cases are chosen based on the outcomes of the executed tests [6], [7], [8], [9], [25], [32], [34], [55]or *nonadaptive*–additional test cases are chosen independently and can be executed in parallel [10], [19], [20], [21], [38].

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 some times even does not work at all. Some problems, e.g., constraints of parameters values in SUT [27], [28], masking effects of multiple failures [4], [5], dynamic requirement for the strength of covering array [11], will cause difficulty to the CT process. To overcome these problems, some works try to make CT more adaptive and flexible.

JieLi [32] 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 [7].

S.Fouché et al., [11] 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 [27], [28] studied the impacts of constraints on CT, and proposed an SAT-based approach that can handle those constraints. Bryce and Colbourn [56] 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 appraoches 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 [57] 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 [58]: First, *statistical* approaches [59], [60], [61]. 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 [62], [63], [64]. 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 [7], [32]. Additionally, a study [65] 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 [58] 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 [66], [67], [68], [69]. Many techniques in CT have been applied on SPL testing [69], among which Henard C, et al. [66] 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 traditional sequential CT.

Empirical studies were conducted on five open-source software subjects. The results show that with our new CT framework, there is a significant reduction on the number of generated test cases when compared to the traditional sequential CT approach, while there is no decline in the quality of the identified MFS. Further, when comparing with another adaptive CT framework *fda-cit* [4], [5], our approach also performed better, especially with better quality of the MFS identification.

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.

Acknowledgments

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References

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

[23] X. Qu, M. B. Cohen, and G. Rothermel, "Configuration-aware regression testing: an empirical study of sampling and prioritiza-

tion," in *Proceedings of the 2008 international symposium on Software testing and analysis*. ACM, 2008, pp. 75–86.

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

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

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

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

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

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

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

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

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

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

[34] K. Shakya, T. Xie, N. Li, Y. Lei, R. Kacker, and R. Kuhn, "Isolating failure-inducing combinations in combinatorial testing using test augmentation and classification," in *Software Testing, Verification and Validation (ICST), 2012 IEEE Fifth International Conference on*. IEEE, 2012, pp. 620–623.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

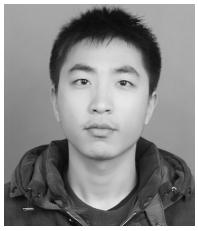
[65] L. S. Ghandehari, Y. Lei, D. Kung, R. Kacker, and R. Kuhn, "Fault localization based on failure-inducing combinations," in *Software Reliability Engineering (ISSRE), 2013 IEEE 24th International Symposium on*. IEEE, 2013, pp. 168–177.

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

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

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

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



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

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

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

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

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

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

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