

## Identifying minimal failure-causing schemas for multiple faults

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Combinatorial testing (CT) ~~has been~~ proven to be effective to reveal the potential failures caused by the interaction of the inputs or options of the System Under Test (SUT). To extend and ~~fully make full use of~~ CT, ~~the~~ theory of Minimal Failure-Causing Schema (MFS) ~~is has been~~ proposed. The use of MFS helps to isolate the root cause of ~~a~~ the failure ~~after CT detection~~, ~~which is desired after detecting them by CT~~. Most ~~existed~~ algorithms ~~that have been~~ based on MFS theory ~~use focus on identifying the MFS to identify in SUT with the a~~ single fault; however, we argue that multiple faults ~~are~~ the more common testing scenario, and under which masking effects may be triggered so that some expected faults will not be observed, ~~normally~~. Traditional MFS theory, as well as ~~the~~ ~~its~~ ~~related~~ identifying algorithms, lack a mechanism to handle such effects; hence, ~~they~~ ~~will may make them~~ incorrectly isolate the MFS in ~~the~~ SUT. To address this problem, we proposed a new MFS model ~~that takes into account with considering~~ multiple faults. We first formally analyse the impact of the multiple faults on ~~the extant~~ existing MFS isolating algorithms, especially ~~in situations where when~~ masking effects ~~are were~~ triggered ~~by between these~~ multiple faults. Based on this, we then ~~develop~~ give an approach that can assist traditional algorithms to better handle ~~the~~ multiple faults testing scenarios. Empirical studies ~~were~~ ~~conducted using with~~ several ~~kinds of~~ open-source software, ~~were conducted~~, which showed ~~ed~~ that multiple faults with masking effects do negatively affect ~~on~~ traditional MFS identifying approaches ~~es~~ and ~~that~~ our approach can help ~~them to~~ alleviate these effects.

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### 1. INTRODUCTION

With the increasing complexity and size of modern software, many factors, such as input parameters and configuration options, can ~~affect influence~~ the behaviour of the SUT. The unexpected faults caused by the interaction ~~of among~~ these factors can make ~~software~~ testing ~~challenging such software a big challenge~~ if the interaction space is too large. In the worst case, we need to examine every possible combination of these factors as each ~~such~~ combination can contain unique faults [Song *et al.* 2012]. While conducting ~~such~~ exhaustive testing is ideal and necessary in theory, it is impractical and ~~not~~ ~~uneconomical~~ ~~in consideration~~.

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Table I. MS word example

id	Highlight	Status bar	Bookmarks	Smart tags	Outcome
1	On	On	On	Off	PASS
2	On	Off	Off	On	PASS
3	Off	On	Off	Off	Fail
4	Off	Off	On	Off	PASS
5	Off	On	On	On	PASS

of the limited testing time and computing resource. One remedy for this problem is combinatorial testing, which systematically samples the interaction space and selects a relatively small set of test cases that cover all the valid iterations, with the number of factors involved in the interaction no more than a prior fixed integer, i.e., the **strength** of the interaction. Many works in CT aims to construct the smallest set of such efficient testing objects [Cohen et al. 1997; Bryce et al. 2005; Cohen et al. 2003], which is also referred to as called a **covering array**.

Once failures are detected by the covering array, it is desired to isolate the failure-inducing combinations in these failed test cases must be isolated. This task is important in CT as it can facilitate the debugging efforts by reducing the code scope that needed for inspection to in-spected [Ghandehari et al. 2012]. However, Only with the information from the covering array sometimes does not clearly far from clear to identify the location and magnitude of the failure-inducing combinations [Colbourn and McClary 2008]. Thus, deeper analysis is needed to be conducted. Consider Take an the following example [Bach and Schroeder 2004], Fig. 1 presents a **two-way** covering array for testing the MS-Word application, in which we want to examine various combinations of options for the MS-Word 'Highlight', 'Status Bar', 'Bookmarks' and 'Smart tags' of MS word. Assume the third test case failed, then we then can get that there are five two-way suspicious combinations that may be responsible for this failure: (Highlight: Off, Bookmarks: Off), (Highlight: Off, Smart tags: Off), (Status Bar: On, Bookmarks: Off), (Status Bar: On, Smart tags: Off), and (Bookmarks: Off, Smart tags: Off). (Note that (Highlight: Off, Status Bar: On) is excluded in this set as it appeared in the fifth passing test case). Without any more information, we cannot figure out which one or more of the combinations some in this suspicious set caused the failure. In fact, taking into account of the higher-strength combination, e.g., (Highlight: Off, Status Bar: On, Smart tags: Off), the problem becomes will grow more complicated.

To address this problem, prior work [Nie and Leung 2011] specifically studied the properties of the minimal failure-causing schemas in SUT, based on which, a further diagnosis by with generating additional test cases was applied that and therefore can identify the MFS in the test case. Other works have been proposed ways to identify the MFS in SUT, which include approaches such as building a tree model [Yilmaz et al. 2006], exploiting the methodology of minimal failure-causing schema [Nie and Leung 2011], ranking suspicious classification combinations based on some rules [Ghandehari et al. 2012], using graphic-based deduction [Martínez et al. 2008], among others, and so on. These approaches can be classified partitioned into two categories [Colbourn and McClary 2008]: **adaptive**-test cases that are chosen based on the outcomes of the executed tests [Nie and Leung 2011; Ghandehari et al. 2012; Niu et al. 2013; Zhang and Zhang 2011; Shakya et al. 2012; Wang et al. 2010; Li et al. 2012] or **nonadaptive**-test cases that are chosen independently and can be executed parallel [Yilmaz et al. 2006; Colbourn and McClary 2008; Martínez et al. 2008; 2009; Fouche' et al. 2009].

The MFS methodology as well as other MFS-identifying approaches mainly focus on the ideal scenario in which that SUT only contains one fault, i.e., the test case under testing can either fails or passes the testing. However, in this paper, we argue that SUT with multiple distinguished faults is the more common testing scenario in practice, and moreover, this do have impacts on the Failure-inducing Combinations Identifying (FCI) approaches. One main impact of multiple faults on FCI approaches is the masking of

effects. A masking effect [Dumlu *et al.* 2011; Yilmaz *et al.* 2013] is an effect ~~in which that~~ some failures prevents test cases from normally checking combinations that are supposed to be tested. Take the Linux command `Grep` for example. ~~We~~<sup>1</sup> noticed that there are two different faults reported in the bug tracker system. The first ~~one~~<sup>2</sup> claims that `Grep` incorrectly matches unicode patterns with '`\<|>`', while the second ~~one~~<sup>2</sup> claims an incompatibility between option '`-c`' and '`-o`'. When we put ~~these~~<sup>is</sup> two scenarios into one test case, only one fault ~~information~~ will be observed, which means another fault is masked by the observed ~~fault~~<sup>one</sup>. This effects will prevent test cases ~~from executing~~ normally ~~executing resulting, consequently make approaches make a~~ in ~~incorrectly~~ judgements of ~~the~~ correlation between the combinations checked in the test case and the fault that ~~has been masked and therefore not observed been prevented to be observed~~.

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As ~~we know known~~ that masking effects negatively affect the performance of FCI approaches, a natural question is how this effect biases the results of ~~these~~<sup>FCI</sup> approaches. In this paper, we formalized the process of identifying ~~the~~ MFS under the circumstances ~~in which that~~ masking effects exist in ~~the~~ SUT and try to answer this question. One insight from the formal analysis is that we cannot completely get away from the impact of ~~the~~ masking effects even if we do exhaustive testing. ~~But Furthermore,~~ ~~both~~ ignoring the masking effects and regarding multiple faults as one fault ~~are~~ ~~detrimental to~~ ~~are harmful to~~ ~~the for~~ FCI process.

Based on ~~this concern, e insight~~ we proposed a strategy to alleviate this impact. This strategy adopts the divide and conquer framework, ~~i.e.~~, separately handles each fault in ~~the~~ SUT. For a particular fault under analysis, when applying traditional FCI approaches to identify the failure-inducing combinations, we pick the test cases generated by FCI approaches that trigger unexpected faults and replace them with ~~newly~~ regenerated ~~newly~~ test cases. These ~~newly~~ test cases should either pass or trigger the same fault under analysis.

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The key to our approach is to search ~~for a~~ test case that ~~does~~ not trigger unexpected fault-s ~~which that~~ may import ~~the~~ masking effect. To guide the searching process, ~~i.e.~~, to reduce the possibility that the extra generated test case ~~will triggering an~~ unexpected fault, a natural idea is to ~~take learn~~ some characteristics from the existed ~~ing~~ test cases and make the characteristics of the newly searched test case as ~~different as possible much as different~~ from those existed ~~ing~~ test cases which triggered ~~the~~ unexpected fault. To reach this target, we define the *related strength* between the factor and the faults, ~~for which~~ ~~the~~ ~~stronger more~~ the *related strength* is between a factor and a particular fault, the ~~greater the likelihood more that that the~~ factor ~~will is likely to~~ trigger this fault. We then using ~~the~~ integer linear programming (ILP) technique to find a test case which has the ~~least smallest~~ *related strength* ~~with between the~~ unexpected fault.

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To evaluate the performance of our approach, we applied our strategy on the FCI approach FIC BS [Zhang and Zhang 2011]. The subjects we used ~~were are~~ several open-source software ~~found in with~~ the developers' forum in ~~the~~ Source-Forge community. Through studying their bug reports in the bug tracker system as well as their user's manuals ~~guide~~, we built ~~the~~ testing model which can reproduce the reported bugs with specific test cases. We then ~~respectively~~ compare the FCI approach augmented with our strategy (AUGF-CI) ~~to with the~~ traditional FCI approach with these subjects. We further empirically studied the performance of the important component of our strategy ~~searching satisfied test cases.~~ ~~To~~ conduct this study, we compare our AUGF-CI approach with the ~~augmented~~ FCI approach ~~augment~~ by randomly searching satisfied test cases. We finally compared our approach with the existed ~~ing~~ masking handling technique ~~FDA-CIT~~ [Yilmaz *et al.* 2013]. All of these empirical studies showed that our replacing strategy as well as the searching test case component ~~achieved get a~~ better performance than these traditional approaches when

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<sup>1</sup><http://savannah.gnu.org/bugs/?29537>

<sup>2</sup><http://savannah.gnu.org/bugs/?33080>



```

public float foo(int a, int b, int c, int d){ //step 1 will
    cause an exception when b == c float x = (float)a /
    (b - c);

    //step 2 will cause an exception when c < d float y
    = Math.sqrt(c - d);

    return x+y;
}

```

Fig. 1. A toy program with four input parameters

the subject ~~is suffering~~ multiple faults, especially when these faults can import masking effects.

The main contributions of this paper are:

- We studied the impact of the masking effects among multiple faults on the isolation of the failure-inducing combinations in SUT.
- We proposed a divide and conquer strategy of selecting test cases to alleviate the impact of the ~~these~~ effects.
- We designed an efficient test case searching method which can rapidly find a test case that does not trigger ~~an~~ unexpected fault.
- We conducted several empirical studies and showed that our strategy can assist FCI approaches to ~~achieve~~ better performance ~~in~~ identifying failure-inducing combinations in SUT with masking effects.

## 2. MOTIVATING EXAMPLE

~~For convenience, we~~ This section constructed a small program example, ~~for convenience~~ to illustrate the ~~benefits~~ motivation of our approach. Assume we have a method *foo* which has four input pa-rameters: *a*, *b*, *c*, ~~and~~ *d*. ~~These types of these~~ four parameters ~~types~~ are all integers and the values

that they can take are:  $v_a = \{7; 11\}$ ;  $v_b = \{2; 4; 5\}$ ;  $v_c = \{4; 6\}$ ;  $v_d = \{3; 5\}$ . The ~~code~~ detail ~~code~~ of the method is ~~shown~~ listed in Figure 1.

~~Considering~~ Inspecting the simple code in Figure 1, we can find two potential faults: First, in ~~the~~ step 1 we can get an *Arithmetic\_Exception* when *b* is equal to *c*, ~~i.e.~~, *b* = 4 ~~&and~~ *c* = 4, ~~that~~ which makes division by zero. Second, another *Arithmetic\_Exception* will be triggered in step 2 when *c* < *d*, ~~i.e.~~, *c* = 4 ~~&and~~ *d* = 5, which makes square roots of negative numbers. So the expected failure-inducing combinations in this example should be (-, 4, 4, -) and (-, -, 4, 5).

Traditional FCI algorithms do not consider the ~~code detail of the code;~~ instead, they apply black-box testing to test this program, ~~i.e.~~, they feed inputs to those programs and execute them to observe the result. The basic justification behind ~~these~~ approaches is that the failure-inducing combinations for a particular fault ~~must~~ can only appear in those inputs that trigger this fault. ~~As-t~~ Traditional FCI approaches aim at using as few inputs as possible to get the same (or ~~an~~ approximate) result as exhaustive testing, so the results derived from ~~an~~ exhaustive testing set ~~are~~ must be the best that these FCI approaches can ~~achieve~~ reach. Next, we will ~~show~~ illustrate how exhaustive testing works ~~to~~ on identifying the failure-inducing combinations in the program.

We first generate every possible inputs listed in the ~~C~~column “test inputs” of Table II, and their execution results are listed in ~~the result C~~column “result” of Table II. In this ~~C~~column, PASS means that the program runs without any exception under the input in the same row. *Ex 1* indicates that the program triggered an exception corresponding to ~~the~~ step 1 and *Ex 2* indicates the program triggered an exception corresponding to the

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Table II. test inputs and their corresponding result

id	test inputs	results	id	test inputs	result
1	(7, 2, 4, 3)	PASS	13	(11, 2, 4, 3)	PASS
2	(7, 2, 4, 5)	Ex 2	14	(11, 2, 4, 5)	Ex 2
3	(7, 2, 6, 3)	PASS	15	(11, 2, 6, 3)	PASS
4	(7, 2, 6, 5)	PASS	16	(11, 2, 6, 5)	PASS
5	(7, 4, 4, 3)	Ex 1	17	(11, 4, 4, 3)	Ex 1
6	(7, 4, 4, 5)	Ex 1	18	(11, 4, 4, 5)	Ex 1
7	(7, 4, 6, 3)	PASS	19	(11, 4, 6, 3)	PASS
8	(7, 4, 6, 5)	PASS	20	(11, 4, 6, 5)	PASS
9	(7, 5, 4, 3)	PASS	21	(11, 5, 4, 3)	PASS
10	(7, 5, 4, 5)	Ex 2	22	(11, 5, 4, 5)	Ex 2
11	(7, 5, 6, 3)	PASS	23	(11, 5, 6, 3)	PASS
12	(7, 5, 6, 5)	PASS	24	(11, 5, 6, 5)	PASS

Table III. Identified failure-inducing combinations and their corresponding Exception

Failure-inducing combinations	Exception
(-, 4, 4, -)	Ex 1
(-, 2, 4, 5)	Ex 2
(-, 3, 4, 5)	Ex 2

step 2. ~~From~~ According to the data listed in Table II, we can ~~determine~~ figure out that (-, 4, 4, -) must be the failure-inducing combination of Ex 1 as all the inputs that triggered Ex 1 contain this combination. Similarly, the combination (-, 2, 4, 5) and (-, 3, 4, 5) must be the failure-inducing combinations of the Ex 2. We listed these three combinations and their corresponding exceptions in Table III.

Note that in this case we did ~~not~~ get the expected result with traditional FCI approaches in this case. The failure-inducing combinations we got for Ex 2 are (-, 2, 4, 5) and (-, 3, 4, 5), re-spectively, instead of the expected combination (-, -, 4, 5). So why ~~did we fail to get~~ we failed in getting the (-, -, 4, 5)? The reason lies in input 6: (7, 4, 4, 5) and input 18: (11, 4, 4, 5). These two in-puts contain the combination (-, -, 4, 5), but they didn't trigger the Ex 2; instead, Ex 1 was triggered.

Now let us get back to the source code of foo. We can find that if Ex 1 is triggered, it will stop executing the remaining code and report the exception information. In another word, Ex 1 has a higher fault level than Ex 2, so that Ex 1 may mask Ex 2. Let us re-examine the combination (-, -, 4, 5): if we supposed that input 6 and input 18 should trigger Ex 2 if they didn't trigger Ex 1, then we can conclude that (-, -, 4, 5) should be the failure-inducing combination of the Ex 2, which is identical to the expected one.

However, we cannot validate the supposition, i.e., that input 6 and input 18 should trigger Ex 2 if it they didn't trigger Ex 1, unless we have fixed the code that triggers Ex 1 and then re-executed all the test cases. So in practice, when we do not have enough resources to re-execute all the test cases again and again or can only ~~dotake~~ black-box testing, ~~thea~~ more economical and efficient approach to alleviate the masking effect on FCI approaches is desired.

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### 3. FORMAL MODEL

This section presents some definitions and propositions ~~forte-give~~ a formal model to solve the for-the FCI problem.

#### 3.1. Failure-causing Schemas in CT

Assume that the SUT is influenced by  $k$  parameters, and each parameter  $p_i$  has  $a_i$  discrete values from the finite set  $V_i$ , i.e.,  $a_i = |V_i|$  ( $i = 1, 2, \dots, k$ ). Some of the definitions below ~~wereare~~ originally defined in [Nie and Leung [2011b]].



**Definition 3.1.** A test case of the SUT is an array of  $k$  values, one for each parameter of the SUT, which is denoted as a  $k$ -tuple  $(v_1, v_2, \dots, v_k)$ , where  $v_1 \in V_1, v_2 \in V_2 \dots v_k \in V_k$ .

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

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We consider ~~the fact that~~ the abnormally executed test cases to be a fault. It can be a thrown exception, compilation error, assertion failure, or constraint violation. When faults are triggered by some test cases, we need what is desired is to determine figure out the cause of these faults, and hence some subsets of this test case must should be analysed.

**Definition 3.2.** For the SUT, the  $t$ -tuple  $(-, v_{k1}, \dots, v_{kt}, \dots)$  is called a  $t$ -value schema ( $0 < t \leq k$ ) when some  $t$  parameters have fixed values and the others can take on their respective allowable values, represented as “-”.

In effect a test case itself is a  $t$ -value schema, when  $t = k$ . Furthermore, if a test case contains a schema, i.e., every fixed value in the combination is in this test case, we say this test case hits the schema.

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**Definition 3.3.** Let  $c_l$  be a  $l$ -value schema,  $c_m$  be an  $m$ -value 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 *parent-schema* of  $c_l$ , which can be denoted as  $c_l < c_m$ .

For example, in the motivation example section, the two-value schema  $(-, 4, 4, -)$  is a sub-schema of the three-value schema  $(-, 4, 4, 5)$ , that is,  $(-, 4, 4, -) < (-, 4, 4, 5)$ .

**Definition 3.4.** If all test cases contain a schema, say  $c$ , and trigger a particular fault, say  $F$ , then we call this schema  $c$  the *failure-causing schema* for  $F$ . Additionally, if none of the sub-schema of  $c$  is the *failure-causing schema* for  $F$ , we then call the schema  $c$  the *Minimal Failure-causing Schema*, i.e., the (MFS) for  $F$ .

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In fact, MFS is identical to the failure-inducing combinations we discussed previously. Figuring this out can eliminate all details that are irrelevant to the cause of the ~~causing the~~ failure and, hence, facilitate the debugging efforts.

Some notions used later are listed below for convenient reference in the following for the convenience of reference:

- $k$ : the number of parameters that influence the SUT.
- $V_i$ : the set of discrete values that the  $i$ th factor of the SUT can take.
- $T^*$ : The exhaustive set of test cases for the SUT. For an SUT with  $k$  factors, and each factor can take  $|V_i|$  values, the number of this set of test cases  $T^*$  is  $\prod_{i=1}^k |V_i|$ .
- $L$ : the number of faults that contained in the SUT.
- $F_m$ : the  $m$ th fault in the SUT; for different faults, we can differentiate them from their exception traces or other buggy information.
- $T_{F_m}$ : All the test cases that can trigger the fault  $F_m$ .
- $T(c)$ : All the test cases that can hit (contain) the schema  $c$ . Based on the definition of MFS, we know can learn that if schema  $c$  is MFS for  $F_m$ , then  $T(c)$  must be subsumed by  $T_{F_m}$ .
- $I(t)$ : All the schemas that are hit in the test case  $t$ , e.g.,  $I((111)) = \{(1--)(-1-)(--1)(11-)(1-1)(-11)(111)\}$ .
- $I(T)$ : All the schemas that are hit in a set of test cases  $T$ , i.e.,  $I(T) = \bigcup_{t \in T} I(t)$ .

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- | —  $S(T)$ : All the schemas that are only hit in the set of test cases. [It](#) is important to note that this set is different from  $I(T)$ , as the schemas hit by the test cases in  $T$  can also be hit by other test cases that [do not](#) belong to this set. In fact,  $S(T)$  is computed by  $\{c | c \in I(T) \text{ and } c \notin (IT^* \setminus T)\}$ .



$\{c; s.t.: c' \in \mathcal{S}(T)\}$ . For this set, we can still have  $c \in M(\mathcal{S}(T))$   $T(c) = T$ . We also prove this

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Table V. Example of the minimal schemas

$T$	$S(T)$	$C(T)$
(0, 0, 0, 0)	(0, 0, 0, 0)	(0, 0, 0, -)
(0, 0, 0, 1)	(0, 0, 0, 1)	(0, 0, -, 0)
(0, 0, 1, 0)	(0, 0, 1, 0)	
	(0, 0, 0, -)	
	(0, 0, -, 0)	

by two steps, first and obviously,  $\neg c \in M(S(T)) \implies T(c) \subset I(c)$ . Then, we just need to prove that  $\bigcup_{c \in S(T)} I(c) \subset \bigcup_{c \in M(S(T))} T(c)$ . In fact,  $\bigcup_{c \in S(T)} I(c) \subset \bigcup_{c \in M(S(T))} T(c)$ . According to the Proposition 3.5,  $T(c) \subset T(c)$ . So for any test case  $t \in \bigcup_{c \in S(T)} T(c)$ , as we have either  $\exists c \in S(T) \setminus M(S(T))$ ;  $s.t.$ ;  $t \in T(c)$  or  $\exists c \in M(S(T))$ ;  $s.t.$ ;  $t \in T(c)$ . Both cases can deduce  $t \in \bigcup_{c \in M(S(T))} T(c)$ . So,  $\bigcup_{c \in S(T)} T(c) \subset \bigcup_{c \in M(S(T))} T(c)$ . Hence,  $\bigcup_{c \in S(T)} T(c) = \bigcup_{c \in M(S(T))} T(c)$ , and  $M(S(T))$  is the set of schemas that holds this proposition.  $\square$

For example, Table V lists the  $S(T)$  and minimal schemas  $C(T)$  for the set of test cases  $T$ . We can see that for any other schemas not in  $C(T)$ , either we can find a test case not in  $T$  hit the schema, e.g., (0,0,-,-) with the test case (0,0,1,1) not in  $T$ , or that is the parent schema of one of the two minimal schemas, e.g., (0,0,0,0) the parent schema of both (0,0,0,-) and (0,0,-,0).

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Let  $T_{F_m}$  denotes the set of all the test cases triggering fault  $F_m$ , then  $C(T_{F_m})$  actually is the set of MFS of  $F_m$  by definition of MFS.

From the construction process of  $C(T)$ , one observation is that the minimal schemas  $C(T)$  is the subset of the schemas set  $S(T)$ , i.e.,  $C(T) \subset S(T)$ , and for any schema in  $S(T)$ , it either belongs to  $C(T)$ , or is the parent schema of one element of  $C(T)$ . Then, we can have the following proposition.

**PROPOSITION 3.7.** For any test cases set  $T$  and schema  $c$ , if any test case hit  $c$  is in the set  $T$ , i.e.,  $T(c) \subset T$ , then it must be that  $c \in C(T)$ .

**PROOF.** We first have  $c \in C(T(c))$ , this is obviously and in fact the minimal schemas for the test cases set  $T(c)$  only contain one schema, which is exactly  $c$  itself. As discussed previously, we have  $C(T(c)) \subset S(T(c))$ , so it must be  $c \in S(T(c))$ .

Then as  $T(c) \subset T$ , it follows  $S(T(c)) \subset S(T)$  by definition. In detail,  $S(T(c)) = \{c/c \in I(T(c)) \text{ and } c' \in (IT^* \setminus T(c))\}$ , so  $S(T(c)) \subset \{c/c \in I(T) \text{ and } c' \in (IT^* \setminus T)\}$ , which is exactly  $S(T)$ .

So as  $c \in S(T(c))$  and hence  $c \in S(T)$ .  $\square$

For two different sets of test cases, there exist some relationships between the minimal schemas of these two sets that varies in the relevancy between with respect to these two different sets of test cases. In fact, there are three possible associations between two different sets of test cases: inclusion, disjointed, and intersection, as listed in Figure 2. We didn't list the condition for that two sets that are identical, because on that condition the minimal schemas must also be identical. To discuss the properties of the relationship of the minimal schemas between two different sets of test cases is important as we will learn later the masking effects between multiple faults that will make the MFS identifying process work incorrectly works, i.e., these FCI approaches may isolate the minimal schemas for the set of test cases which are biased from the expected failing set of test cases. And these properties can help us to figure out the

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| impact of masking effects on the FCI ap-

ACM Transactions on Embedded Computing Systems, Vol. 9, No. 4, Article 39, Publication date: March 2010.

Table VI. Example of the scenarios

$T_I$	$T_K$	$T_I$	$T_K$
(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)
(0, 0, 1)	(0, 0, 1)	(0, 0, 1)	(0, 0, 1)
(0, 1, 0)	(0, 1, 0)	(0, 1, 0)	(0, 1, 0)
	(0, 1, 1)		(1, 1, 0)
			(1, 1, 1)
$C(T_I)$	$C(T_K)$	$C(T_I)$	$C(T_K)$
(0, 0, -)	(0, -, -)	(0, 0, -)	(0, 0, -)
(0, -, 0)		(0, -, 0)	(0, -, 0)
			(1, 1, -)

proaches. Next, we will separately discuss the relationship between minimal schemas under the three conditions.

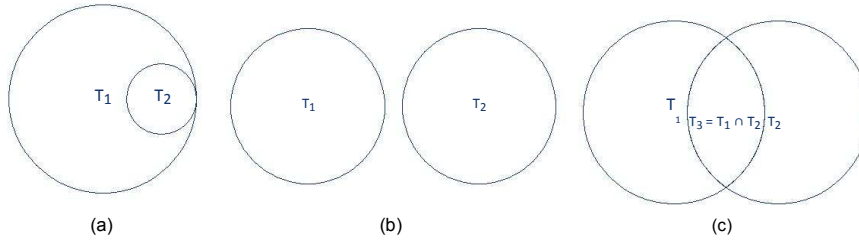


Fig. 2. Test Suites relationships

### 3.2. Inclusion

It is the first relationship corresponding to Fig. 2(a). We can have the following proposition with two sets of test cases which have the inclusion relationship.

**PROPOSITION 3.8.** For two sets of test cases  $T_I$  and  $T_K$ , assume that  $T_I \subset T_K$ . Then, we have

$$\forall c_I \in \mathcal{A}(T_I) \text{ either we have } c_I \in \mathcal{A}(T_K) \text{ or have } \exists c_K \in \mathcal{A}(T_K); \text{ s.t.: } c_K < c_I.$$

**PROOF.** Obviously for  $\forall c_I \in \mathcal{A}(T_I)$ , we can get  $T(c_I) \subset T_I \subset T_K$ . According to the proposition 3.7, we can have  $c_I \in \mathcal{A}(T_K)$ . So this proposition holds as the schema in  $\mathcal{A}(T_K)$  either is also in  $\mathcal{A}(T_I)$ , or must be the parent of some schemas in  $\mathcal{A}(T_I)$ .  $\square$

Based on this proposition, in fact, the schema  $c_K \in \mathcal{A}(T_K)$  remains with the following three possible relationships with  $\mathcal{A}(T_I)$ : (1)  $c_K \in \mathcal{A}(T_I)$ , or (2)  $\exists c_I \in \mathcal{A}(T_I); \text{ s.t.: } c_K < c_I$ , or (3)  $c_I \in \mathcal{A}(T_I); \text{ s.t.: } c_K < c_I \text{ or } c_K = c_I; \text{ or } c_I < c_K$ . For the third case, we call  $c_K$  is irrelevant to  $\mathcal{A}(T_I)$ .

We illustrate these scenarios in Table VI. There are two parts in this table, with each part showing two sets of test cases:  $T_I$  and  $T_K$ , which have  $T_I \subset T_K$ . For the left part, we can see that in the schema in  $\mathcal{A}(T_I)$ : (0, 0, -) and (0, -, 0), both are the parent of the schema of the one in  $\mathcal{A}(T_K)$ : (0, -, -). While for the right part, the schemas in  $\mathcal{A}(T_I)$ : (0, 0, -) and (0, -, 0) are both also in  $\mathcal{A}(T_K)$ . Furthermore, one schema in  $\mathcal{A}(T_K)$ : (1, 1, -) is irrelevant to  $\mathcal{A}(T_I)$ .

### 3.3. Disjoint

This relationship is corresponding to the Fig. 2(b). For two different sets of test cases, one obvious property is listed as follows:



VII. Disjoint  
Table Examples of  
disjoint examples

$T_l$	$T_k$
(0, 0, 0)	(1, 0, 0)
(0, 1, 0)	(1, 0, 1)
	(1, 1, 0)
$C(T_l)$	$C(T_k)$
(0, -, 0)	(1, 0, -)
	(1, -, 0)

PROPOSITION 3.9.

For two test cases set  $T_1, T_2$ , if  $T_1 \cap T_2 = \emptyset$ , we have,  $\mathcal{Q}(T_1) \cap \mathcal{Q}(T_2) = \emptyset$ . Without loss of generality, we let  $T_1 = \{s_1, s_2, \dots, s_n\}$  and  $T_2 = \{t_1, t_2, \dots, t_m\}$ . We can learn that  $T_1 \cap T_2 = \emptyset$ .

This property tells that the minimal schemas of two disjoint test cases should be irrelevant to each other. Table VII list the shows an example of this scenario. We can learn from this table that for two different test cases sets  $T_l, T_k$ , their minimal schemas, i.e., (0, -, 0) and (1, 0, -), (1, -, 0), respectively, are irrelevant to each other.

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### 3.4. Intersect

This relationship is corresponding to the Fig. 2(c). This scenario is the most common scenario for two sets of test cases, but is also the most complicated scenario for analysis.

We assume that  $T_1 \cap T_2 = T_3$  as depicted in Fig. 2(c). Then we can have the following properties:

PROPOSITION 3.10. For two intersecting sets of test cases  $T_1$  and  $T_2$  (this two-set is neither identical nor do the members subsuming each other), it must have  $\exists c_1 \in \mathcal{Q}(T_1)$  and  $c_2 \in \mathcal{Q}(T_2)$ , s.t.  $c_1$  and  $c_2$  are irrelevant.

PROOF. Firstly, we can learn that  $\mathcal{Q}(T_1 | T_3)$  are irrelevant to  $\mathcal{Q}(T_2 | T_3)$ , as  $(T_1 | T_3) \cap (T_2 | T_3) = \emptyset$ .

As  $\mathcal{Q}(T_1 | T_3)$  is either identical to some schemas in  $\mathcal{Q}(T_1)$  or be the parent schemas of them, then if some of them are identical, i.e.,  $\exists c; s.t.; c \in \mathcal{Q}(T_1 | T_3)$  and  $c \in \mathcal{Q}(T_1)$ , then these schemas  $c$  must be irrelevant to  $\mathcal{Q}(T_2)$  as  $(T_1 | T_3) \cap (T_2 | T_3) = \emptyset$ . This is also holds if  $\mathcal{Q}(T_2 | T_3)$  is identical to some schemas in  $\mathcal{Q}(T_2)$ .

Next, if both  $\mathcal{Q}(T_1 | T_3)$  and  $\mathcal{Q}(T_2 | T_3)$  are parent schemas of some of  $\mathcal{Q}(T_1)$  and  $\mathcal{Q}(T_2)$ , respectively, without loss of generality, we let  $c_1 \prec c_{1-3}$ , ( $c_{1-3} \in \mathcal{Q}(T_1 | T_3)$  and  $c_1 \in \mathcal{Q}(T_1)$ ) and  $c_2 \prec c_{2-3}$ , ( $c_{2-3} \in \mathcal{Q}(T_2 | T_3)$  and  $c_2 \in \mathcal{Q}(T_2)$ ). Then, these corresponding sub-schemas in  $\mathcal{Q}(T_1)$  and  $\mathcal{Q}(T_2)$ , i.e.,  $c_1$  and  $c_2$  respectively, must also be irrelevant to each other. This is because  $T(c_1) \supset T(c_{1-3})$  and  $T(c_2) \supset T(c_{2-3})$ . And as  $T(c_{1-3}) \cap T(c_{2-3}) = \emptyset$ , so  $T(c_1) \cap T(c_2) = \emptyset$ . This is because  $T(c_1)$  and  $T(c_2)$  are neither identical nor subsuming each other, this which also implies that  $c_1$  and  $c_2$  are irrelevant to each other.

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For example, Table VIII shows two test cases that interact with each other at test case (1,0,0), but their minimal schemas, (1,0,-) and (1,-,0), respectively, are irrelevant to each other.

3.11. For two intersecting set of test cases  $T_1$  and  $T_2$ , and let  $T_3 = T_1 \cap T_2$ .

If we can find  $\exists c_1 \in \mathcal{Q}(T_1)$  and  $c_2 \in \mathcal{Q}(T_2)$ , s.t.,  $c_1$  is identical to  $c_2$ , then it must have  $c_1 = c_2 \in \mathcal{Q}(T_3)$ .

PROOF. As we get see that the identical schema must share the identical test cases, then the only identical test cases between  $T_1$  and  $T_2$  is  $T_3$ . So the only possible

identical schemas between  $\mathcal{Q}(T_1)$  and  $\mathcal{Q}(T_2)$  is in  $\mathcal{Q}(T_3)$ .





ACM Transactions on Embedded Computing Systems, Vol. 9, No. 4, Article 39, Publication date: March 2010.

Table VIII. Example of Intersection by irrelevant examples

$T_1$	$T_2$
(1, 0, 0)	(1, 0, 0)
(1, 0, 1)	(1, 1, 0)
$C(T_1)$	$C(T_2)$
(1, 0, -)	(1, -, 0)

Table IX. Example of Intersection by identical examples

$T_1$	$T_2$	$T_3 = T_1 \cap T_2$
(0, 1, 0)	(0, 0, 1)	(1, 1, 1)
(1, 1, 0)	(1, 1, 0)	(1, 1, 1)
(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
$C(T_1)$	$C(T_2)$	$C(T_3)$
(-, 1, 0)	(0, 0, -)	(1, 1, -)
(1, 1, -)	(1, 1, -)	(1, 1, -)

Table X. Example of Intersection by subsuming examples

$T_1$	$T_2$	$T_3 = T_1 \cap T_2$
(0, 1, 0)	(0, 0, 0)	(1, 0, 1)
(1, 0, 0)	(1, 0, 0)	(1, 0, 1)
(1, 0, 1)	(1, 0, 1)	(1, 1, 0)
(1, 1, 0)	(1, 1, 0)	(1, 1, 1)
$C(T_1)$	$C(T_2)$	$C(T_3)$
(-, 1, 0)	(-, 0, 0)	(1, 0, -)
(1, 0, -)	(1, -, -)	(1, -, 0)
(1, -, 0)		

We must know that this proposition holds when some schemas in  $(T_1 \cap T_2)$  are identical to some schemas in  $\mathcal{C}(T_1)$  and  $\mathcal{C}(T_2)$ .

For example, Table IX shows two test cases that interact with each other at test cases (1,1,0) and (1,1,1), and they have identical minimal schemas, i.e., (1,1,-), which is also the minimal schema in  $\mathcal{C}(T_3)$ .

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**PROPOSITION 3.12.** For two intersecting sets of test cases  $T_1$  and  $T_2$ , and let  $T_3 = T_1 \cap T_2$ , if there we can find  $\exists c_1 \in \mathcal{C}(T_1)$  and  $c_2 \in \mathcal{C}(T_2)$ , s.t.,  $c_1$  is the parent-schema of  $c_2$ , then it must have  $c_1 \in \mathcal{C}(T_3)$ . (and vice versa).

$$\cap \in \mathcal{C}$$

**PROOF.** We have proved previously if two schemas have a subsuming relationship, then their test cases must also have an inclusion relationship. And as the only inclusion relationship between  $T_1$  and  $T_2$  is that  $T_3 \subset T_1$  and  $T_3 \subset T_2$ . So the parent schemas must be in  $\mathcal{C}(T_3)$ .  $\square$

It is noted that this proposition holds when some schema in  $\mathcal{C}(T_3)$  is identical in  $\mathcal{C}(T_1)$  (or  $\mathcal{C}(T_2)$ ), and simultaneously the same schemas in  $\mathcal{C}(T_3)$  must be the parent-schema of the minimal schemas of another set of test cases, i.e.,  $\mathcal{C}(T_2)$  (or  $\mathcal{C}(T_1)$ ).

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Table X illustrates this scenario, in which the minimal schemas of  $T_1$ : (1,0,-), (1,-,0), which are also the schemas in  $\mathcal{C}(T_3)$ , is the parent schema of the minimal schema of  $T_2$ : (1,-,-).

It is noted that these three conditions can simultaneously appear when two sets of

test cases intersect with each other.

ACM Transactions on Embedded Computing Systems, Vol. 9, No. 4, Article 39, Publication date: March 2010.

### 3.5. Identifying the MFS

According to this analysis, we can determine that  $C(T_{F_m})$  actually is the set of failure-causing schemas of  $F_m$ . Then in theory, if we want to accurately figure out the MFS in the SUT, we need to exhaustively execute each possible test case, and collect the failing test cases  $T_{F_m}$ . This is impossible in practice, especially when the testing space is very large.

So for traditional FCI approaches, they need to select the subset of the exhaustive test cases, and then either use an assumption to make prediction of the remaining test cases or just give a suspicious ranking. As giving a suspicious ranking can also be regarded as a special case of making a prediction (with computing the possibility), so we next only formally describe the mechanism of FCI approaches belonging to the first type. We refer

to the observed failing test case as  $T_{fail_{observed}}$ , and refer to the remaining failing test cases based on prediction as  $T_{fail_{predicted}}$ . We also denote the actually entire failing test cases as  $T_{fail}$ . Then the MFS identified by FCI approaches can be depicted as:

For each FCI approach, the way it predicts the  $T_{fail_{predicted}}$  according to observed failing test cases varies; further-more, as the test cases it generates are different, the

failing test cases observed by different test cases, i.e.,  $T_{fail_{observed}}$  also varies. We take an example using the OFOT approach to illustrate this formula.

Suppose that the SUT has 3 parameters, each of which can take 2 values. And assume the test case (1, 1, 1) failed. Then we can describe the FCI process as shown in Table XI. In this table, test case  $t$  failed, and OFOT mutated one factor of the  $t$  one time to generate new test cases:  $t_1$ ;  $t_2$ ;  $t_3$ . It found the  $t_1$  passed, which indicates that this test case breaks the MFS in the original test case  $t$ . So, the (1, -, -) should be one failure-causing factor, and as the other mutating processes all failed, this means no other failure-inducing factors were broken; therefore, the MFS in  $t$  is (1, -, -).

Now let us explain this process with our formal model. Obviously the  $T_{fail_{observed}}$  is  $\{(1, 1, 1), (1, 0, 1), (1, 1, 0)\}$ . And as having found (0, -, -) broke the MFS, hence by theo-

ry [Nie and Leung 2011a], all the test cases that contain (0, -, -) should pass the test cases (This conclusion is built on the assumption that the SUT just contains one failure-causing schema). As a result, (0, 1, 1), (0, 0, 1), (0, 1, 0), (0, 0, 0) should pass the testing. Further, as obviously the test case either passes or fails the testing (we label the skipping the testing as a special case of failing), so the remaining test case (1, 0, 0) will be predicted to fail as failing.

i.e.,  $T_{fail_{predicted}}$  is  $\{(1, 0, 0)\}$ . Taking together, the MFS using the OFOT strategy can be described as:  $C(T_{fail_{observed}} \cup T_{fail_{predicted}}) = C(\{(1; 1; 1); (1; 0; 1); (1; 1; 0); (1; 0; 0)\}) = (1, -, -)$ .

which is identical to the

Table XI. OFOT with our strategy

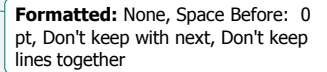
original test case	Outcome		
$t$	1	1	1
<b>observed</b>			
$t_1$	0	1	1
$t_2$	1	0	1
$t_3$	1	1	0
<b>predicted</b>			
$t_4$	0	0	1
$t_5$	0	1	0
$t_6$	1	0	0
$t_7$	0	0	0

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Similarly, other FCI approaches can also be modeled ~~into~~ this formal description. We will not discuss in detail ~~discuss~~ how to model each FCI approach as this is not the point of this paper. It is noted that the test cases FCI predicts to be failing ~~isare~~ not always identical



to the actually failing test cases. In fact, we can generally depict the process of FCI approaches [as shown in Fig. 3](#).

areas  $A$   $B$   $C = T_1$  area  $D$   $B$   $C = T_2$  and area  $B$   $C = T_1$   $T_2 = T_3$ .  
 learned previously that this scenario makes the schemas identified in  
 We  $T$   $1$   $2$   $3$   $4$   $5$   $6$   $7$   $8$   $9$   $10$   $11$   $12$   $13$   $14$   $15$   $16$   $17$   $18$   $19$   $20$   $21$   $22$   $23$   $24$   $25$   $26$   $27$   $28$   $29$   $30$   $31$   $32$   $33$   $34$   $35$   $36$   $37$   $38$   $39$   $40$   $41$   $42$   $43$   $44$   $45$   $46$   $47$   $48$   $49$   $50$   $51$   $52$   $53$   $54$   $55$   $56$   $57$   $58$   $59$   $60$   $61$   $62$   $63$   $64$   $65$   $66$   $67$   $68$   $69$   $70$   $71$   $72$   $73$   $74$   $75$   $76$   $77$   $78$   $79$   $80$   $81$   $82$   $83$   $84$   $85$   $86$   $87$   $88$   $89$   $90$   $91$   $92$   $93$   $94$   $95$   $96$   $97$   $98$   $99$   $100$   $101$   $102$   $103$   $104$   $105$   $106$   $107$   $108$   $109$   $110$   $111$   $112$   $113$   $114$   $115$   $116$   $117$   $118$   $119$   $120$   $121$   $122$   $123$   $124$   $125$   $126$   $127$   $128$   $129$   $130$   $131$   $132$   $133$   $134$   $135$   $136$   $137$   $138$   $139$   $140$   $141$   $142$   $143$   $144$   $145$   $146$   $147$   $148$   $149$   $150$   $151$   $152$   $153$   $154$   $155$   $156$   $157$   $158$   $159$   $160$   $161$   $162$   $163$   $164$   $165$   $166$   $167$   $168$   $169$   $170$   $171$   $172$   $173$   $174$   $175$   $176$   $177$   $178$   $179$   $180$   $181$   $182$   $183$   $184$   $185$   $186$   $187$   $188$   $189$   $190$   $191$   $192$   $193$   $194$   $195$   $196$   $197$   $198$   $199$   $200$   $201$   $202$   $203$   $204$   $205$   $206$   $207$   $208$   $209$   $210$   $211$   $212$   $213$   $214$   $215$   $216$   $217$   $218$   $219$   $220$   $221$   $222$   $223$   $224$   $225$   $226$   $227$   $228$   $229$   $230$   $231$   $232$   $233$   $234$   $235$   $236$   $237$   $238$   $239$   $240$   $241$   $242$   $243$   $244$   $245$   $246$   $247$   $248$   $249$   $250$   $251$   $252$   $253$   $254$   $255$   $256$   $257$   $258$   $259$   $260$   $261$   $262$   $263$   $264$   $265$   $266$   $267$   $268$   $269$   $270$   $271$   $272$   $273$   $274$   $275$   $276$   $277$   $278$   $279$   $280$   $281$   $282$   $283$   $284$   $285$   $286$   $287$   $288$   $289$   $290$   $291$   $292$   $293$   $294$   $295$   $296$   $297$   $298$   $299$   $300$   $301$   $302$   $303$   $304$   $305$   $306$   $307$   $308$   $309$   $310$   $311$   $312$   $313$   $314$   $315$   $316$   $317$   $318$   $319$   $320$   $321$   $322$   $323$   $324$   $325$   $326$   $327$   $328$   $329$   $330$   $331$   $332$   $333$   $334$   $335$   $336$   $337$   $338$   $339$   $340$   $341$   $342$   $343$   $344$   $345$   $346$   $347$   $348$   $349$   $350$   $351$   $352$   $353$   $354$   $355$   $356$   $357$   $358$   $359$   $360$   $361$   $362$   $363$   $364$   $365$   $366$   $367$   $368$   $369$   $370$   $371$   $372$   $373$   $374$   $375$   $376$   $377$   $378$   $379$   $380$   $381$   $382$   $383$   $384$   $385$   $386$   $387$   $388$   $389$   $390$   $391$   $392$   $393$   $394$   $395$   $396$   $397$   $398$   $399$   $400$   $401$   $402$   $403$   $404$   $405$   $406$   $407$   $408$   $409$   $410$   $411$   $412$   $413$   $414$   $415$   $416$   $417$   $418$   $419$   $420$   $421$   $422$   $423$   $424$   $425$   $426$   $427$   $428$   $429$   $430$   $431$   $432$   $433$   $434$   $435$   $436$   $437$   $438$   $439$   $440$   $441$   $442$   $443$   $444$   $445$   $446$   $447$   $448$   $449$   $450$   $451$   $452$   $453$   $454$   $455$

However, even though each FCI approach tries its best to identify the MFS as accurate as possible, masking effects raised from the test cases will resultmake in their efforts being in vain. We next will discusses the masking problem and how it affects the FCI approaches.

*Definition 4.1.* A *masking effect* is the an effect that results when while a test case  $t$  hits an MFS for a particular fault, but the however,  $t$  does not didn't trigger the expected fault because an other fault was triggered ahead of it that which prevents  $t$  from being to be normally checked.

Taking the masking effects into account, when identifying the MFS for a specific fault,

| say,  $F_m$ , we should not ignore these test cases which should have triggered  $F_m$  if

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Table XII. Masking effects for exhaustive testing

$T_1$	$mask(1)$	$T_*$
(1, 1, 1, 1)	(1, 1, 0, 0)	(0, 1, 0, 0)
(1, 1, 1, 0)	(0, 1, 1, 1)	(0, 0, 0, 0)
(1, 1, 0, 1)		(1, 0, 0, 0)
		(1, 0, 1, 1)
		(0, 0, 1, 1)
actual MFS for 1	regard as one fault	distinguish faults
$\bigcup_{i=1}^L mask(i)$	$\bigcup_{i=1}^L mask(i)$	$C(T_1)$
(-, 1, 1, 1)	(-, -, 0, 0) $\cup$ (1, 1, -, -)	(1, 1, -, 1)
	(-, -, 1, 1)	(1, 1, 1, -)

they didn't trigger other faults. We call these test cases  $T_{mask(F_m)}$ . Hence, the MFS for fault  $F_m$  should be  $(T_{F_m} \cup T_{mask(F_m)})$ .

As an example, in the motivation example in section 2, the  $F_{mask(Ex2)}$  is  $\{(7,4,4,5), (11,4,4,5)\}$ . So the MFS for  $Ex2$  is  $C(T_{Ex2} \cup T_{mask(Ex2)})$ , which is  $(-, -, 4, 5)$ .

In practice with masking effects, however, it is the MFS, unless we fix some bugs in the SUT and re-execute the test cases to figure out  $T_{mask(F_m)}$ .

In effect for traditional FCI approaches, without the knowledge of  $T_{mask(F_m)}$ , only two strategies can be adopted when facing the multiple faults problem. We will separately analyse the two strategies under exhaustive testing conditions and normal FCI testing conditions.

#### 4.1. Masking effects for exhaustive testing

4.1.1. *Regarded as one fault.* The first one is the most common strategy, as it does not distinguish the faults, i.e., it treats all of the types of faults as one fault-failure, and others as pass.

With this strategy, the minimal schemas we identify are the set  $C(\bigcup_{i=1}^L T_{Fi})$ ,  $L$  is the number of all the faults in the SUT. Obviously,  $T_{F_m} \cup T_{mask(F_m)} \subset \bigcup_{i=1}^L T_{Fi}$ . So in this case, by Proposition 3.8, some schemas we get may be irrelevant to the actual MFS.

As an example, consider the test cases in Table XII. In this example, assume we need to characterize the MFS for error 1. All the test cases that triggered error 1 are listed in the column  $T_1$ ; similarly, we list the test cases that triggered other faults in column  $T_{mask(1)}$  and  $T_*$  respectively, in which the former masked the error 1 while the latter did not. Actually the MFS for error 1 should be  $(1, 1, -, -)$  and  $(-, 1, 1, 1)$  as we listed them in the column *actual MFS for 1*. However, when we use the *take-regard as one fault* strategy, the minimal schemas we get will be  $(-, -, 0, 0)$ ,  $(1, 1, -, -)$ ,  $(-, -, 1, 1)$ , in which the  $(-, -, 0, 0)$  is irrelevant to the actual MFS for error 1 and the  $(-, -, 1, 1)$  is the sub-schema of the actual MFS  $(-, 1, 1, 1)$ .

4.1.2. *Distinguishing faults.* Distinguishing the faults by the exception traces or error code can help make the MFS related to a particular fault. Yilmaz et al. [2013] proposed the *multiple-class* failure characterizing method instead of the *ternary-class* approach to make the characterizing process more accurately. Besides, other approaches can also be easily extended with this strategy for application with multiple faults.

This strategy focuses on identifying the set of  $C(T_{F_m})$ , and as  $T_{F_m} \cup T_{mask(F_m)} \supset T_{F_m}$ , consequently, some schemas that get through this strategy may be the parent-schema of some MFS. Moreover, some MFS may be irrelevant to the schemas we get with this strategy, which means this strategy will ignore these MFS.

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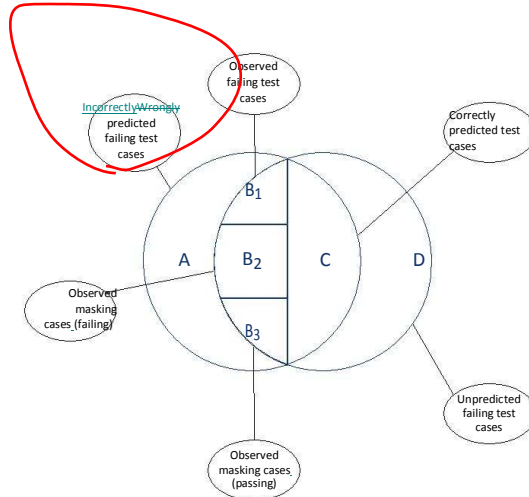


Fig. 4. FCI with masking effects

For the simple example in Table XII, when we using this strategy, we will get the minimal schemas (1, 1, -, 1) and (1, 1, 1, -), which are both the parent schemas of the actual MFS (1,1,-,-), and we will observe that there is no schemas gotten by this strategy have any relationship with the actual MFS (-,1,1,1), which means they were ignored. it ignored the schema.

It is noted that, the motivation example in section 2 actually adopted this strategy, so we see that which made the schemas identified for Ex 2: (-,2,4,5), (-,3,4,5) are the parent-schemas of the correct MFS(-,-,4,5).

#### 4.2. Masking effects for FCI approaches

With masking effects, the scenario of traditional FCI approaches is a bit more complicated than the previous two exhaustive testing scenarios, which can be depicted in the Figure 4. In this figure, areas A, C and D are the same as in Figure 3, and area B is divided into three sub-areas, in which B<sub>1</sub> is still represents the observed failing test cases for the current analysed fault, area B<sub>2</sub> represents the test cases that triggered other faults which masked the current fault, and area B<sub>3</sub> represents the test cases that triggered other faults which did not mask the current fault.

With this model, if we have known which test cases mask the expected fault, i.e., if we have figured out the B<sub>2</sub> and B<sub>3</sub> areas, then the schemas that the FCI approach will identify can be described as C(A B<sub>1</sub> B<sub>2</sub> C). We next denote this result as knowing masking effects.

However, as involvement. Correspondingly, when using the taking regard as one fault strategy, the MFS traditional FCI identify is C(A B<sub>1</sub> B<sub>2</sub> B<sub>3</sub> C). And for the distinguishing faults strategy, the MFS is C(A B<sub>1</sub> C). Next, we will respectively discuss the influence of masking effects on the two strategies.

4.2.1. Using the Taking regard as one fault strategy. For the first strategy: regard as one fault, the impact of masking effects on FCI approaches can be described as shown in Figure 5. To understand the content of this figure, let us go back to the relationship between the minimal schemas of two different sets of test cases. For the knowing masking effects condition, the result identified by the FCI approach, i.e., C(A B<sub>1</sub> B<sub>2</sub> C), is one case of the inter-

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parent-schema, sub-schema, <sup>U</sup> <sup>U</sup> <sup>U</sup> is irrelevant to the actual MFS. And if we then apply the *regard*

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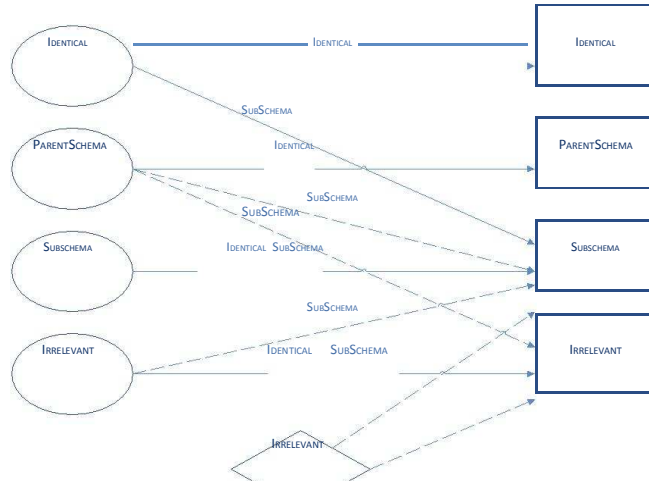


Fig. 5. Masking effects influence on FCI using with regard as one fault

as one fault, the minimal schemas we get are  $(A \ B_1 \ B_2 \ B_3 \ C)$ . Obviously, we have  $A \ B_1 \ B_2 \ B_3 \ C \supset A \ B_1 \ B_2 \ C$ . So the minimal schema gotten by this strategy is either the sub-schema or identical to some schemas from the ones gotten by known masking effects, or exist some schemas irrelevant to all of them. Taking these two properties together, we will get what is shown in Figure 5.

The ellipses in the left column of this figure illustrated the relationship between the schemas identified under the knowing masking effects condition with the actual MFS, which includes the four possibilities: identical, sub-schema, parent-schema, and irrelevant. For each relationship in this part, without loss of generality, we consider

$c_{origin}$  and  $c_m$ .  $c_{origin}$  is the minima schema gotten by knowing masking effects, and  $c_m$  is the actual MFS. Then, when we apply the regard as one fault strategy, we may get some

schemas which are identical or sub-schema of  $c_{origin}$ , say  $c_{new}$  s.t.,  $c_{new} = c_{origin}$  or  $c_{new} < c_{origin}$ . In this figure, we use the directed line to represent these two transformations with different labels in each line. As for the schemas  $c_{new}$  that are irrelevant to all the  $c_{origin}$ , we in the bottom of this figure use a rhombus labeled with "Irrelevant" to represent express them. Then, we must have some relationship between the  $c_{new}$  and actual MFS, which also has four possibilities represented as rectangles in the right column.

Note that there exists two types of directed line, solid line and dashed line, in which

the former indicates that this transformation is deterministic, e.g., if  $c_{origin} < c_m$  and  $c_{new} < c_{origin}$ , then we must have  $c_{new} < c_m$ . The latter type means the transformation is just one of all the possibilities in such condition, e.g., if  $c_{origin}$  irrelevant  $c_m$  and  $c_{new} < c_{origin}$ , then we can have either  $\exists c_m$  is one actual MFS; s.t.  $c_{new} < c_m$  or  $c_{new}$  irrelevant to all actual MFS. (We will later give illustrative examples to illustrate them).

In this figure, only two transformations can make  $\exists c_m$  is one actual MFS; s.t.  $c_{new} = c_m$  or  $c_m < c_{new}$ , which are when  $c_{origin} = c_m$ ,  $c_{new} = c_{origin}$  or  $c_m < c_{origin}$ ,  $c_{new} = c_{origin}$  respectively. This can be easily understood, as to make  $c_{new} = c_m$  or  $c_m < c_{new}$ , according to the proposition 3.11 and 3.12, it must have  $(c_{new}) \supset (B_1 \cup B_2)$ . If after transformation, we get  $c_{new} < c_{origin}$ , then we must have  $\exists t \in B_3$ ; s.t.  $t \in T(c_{new})$ , otherwise, there should behave no changing to the  $c_{origin}$ , and it must have no new schema

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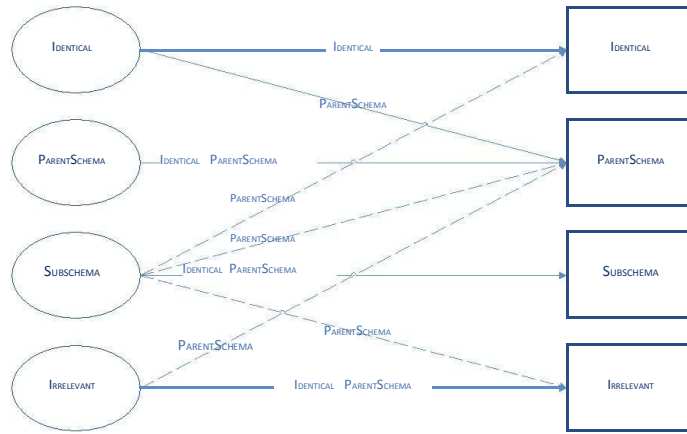


Fig. 6. Masking effects influence on FCI with distinguishing faults

$c_{new}$  that is the sub-schema of  $c_{origin}$ . Consequently,  $(c_{new}) \subset (B_1 \cup B_2)$  if we have  $c_{new} < c_{origin}$ . So in order to make  $c_{new} = c_m$ —or  $T_{c_m} < c_{new}$ , the transformation can only be identical, i.e.,  $c_{new} = c_{origin}$  and must have  $c_{origin} = c_m$  or  $c_m < c_{origin}$ , correspondingly.

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As the identical transformation is simple, so next we will ignore them and just take examples to illustrate the other transformations. Table XIII presents all these possibilities except these identical transformations. This table consists comprises of three parts, with which the upper part giving the test cases for each area in the abstract FCI model. It is noted that we merged the area- $B_1$ ,  $B_2$  and  $C$  areas into one column to the way of computing the minimal schemas of the three approaches—actual MFS, knowing masking effects, regarded as one fault are all dependent on the merging the test cases of these three areas, not on their specific distribution of them. The middle part of this table shows the minimal schemas that using this particular method. And last, the lower part in specific depicts the sample of each possible result of the transformation in the Figure 5. In this part,

$c_m = c_{origin} \rightarrow c_{new} < c_m$  indicates the scenario that the schema  $c_{origin}$  got by knowing masking effects is identical to one actual MFS  $c_m$ . Then, taking regard as one fault, we got  $c_{new} < c_{origin}$ , so and such that we can have  $\exists c_m$  is one actual MFS; s.t.:  $c_{new} < c_m$ . Other formulae in this column can be explained in this way, in which  $c_{new}$  irrele and  $c_{origin}$  irrele means that the schema  $c_{new}$  and  $c_{origin}$  is irrelevant to all the actual MFS, respectively. The mark \* in  $c_m$  and  $c_m$ , respectively, represent these two conditions. The formulae in the last two rows,  $c_{new}^{irrele} < c_m$  and  $c_{new}^{irrele} \text{ irrele}$ , indicate the schemas  $c_{new}^{irrele}$  obtained got by regard as one fault are irrelevant to all the  $c_{origin}$ , in which the former is the subschema of some actual MFS  $c_m$ , while the latter is irrelevant to all of the actual MFS. The \* in the  $c_{origin}$  column means that the  $c_{new}$  is irrelevant to all the  $c_{origin}$ .

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4.2.2. using distinguish strategy. And for the second strategy, distinguish faults, the influence can be described as in Figure 6.

This figure is organised the same way as Figure 5. As with the distinguish faults strategy,

the minimal schemas identified are actually  $\mathcal{Q}(A$

$B_1 \cup C)$ . Obviously  $A \subset B_1$  and  $C \subset B_1$  should be either the parent-

$A \subset B$  or  $B \subset C$ . So under this transformation, the  $c_{new}$  schema or identical to the  $c_{origin}$ .

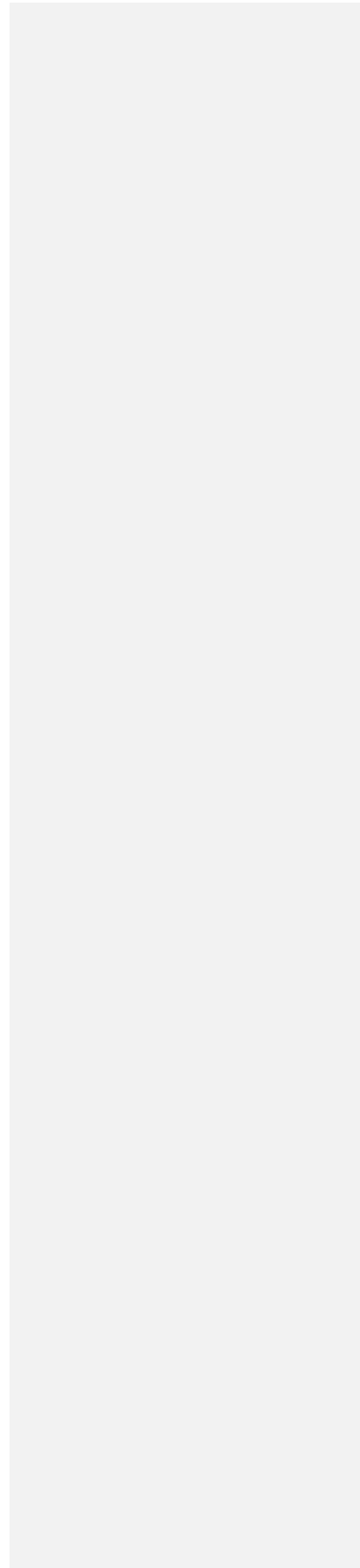


Table XIII. Example of the influence of the regard as one fault for FCI approach

A	B <sub>1</sub>	B <sub>2</sub>	C	B <sub>3</sub>	D
(0,0,0,1,0,0)	(1,1,1,0,0,0)			(1,0,1,0,0,0)	(1,1,0,0,0,0)
(0,0,0,1,1,0)	(1,1,1,0,1,0)			(1,0,1,0,1,0)	(1,1,0,0,1,0)
(0,0,1,0,0,0)	(1,1,1,1,0,0)			(0,0,1,0,1,0)	(1,1,0,1,0,0)
(0,0,1,1,0,0)	(1,1,1,1,1,0)			(0,0,1,1,1,0)	(1,1,0,1,1,0)
	(1,0,1,1,0,0)			(0,1,0,0,0,0)	(0,0,1,1,0,1)
	(1,0,1,1,1,0)			(0,1,0,1,0,0)	(0,1,1,1,0,1)
	(0,0,0,0,1,0)			(0,1,1,0,0,0)	
	(0,0,0,0,0,0)			(0,1,1,1,0,0)	
	(0,0,1,1,1,1)			(1,0,0,0,0,0)	
	(0,1,1,1,1,1)			(1,0,0,0,1,0)	
				(1,1,1,1,1,1)	
				(1,0,1,1,1,1)	
actual MFS					
$\alpha(B_1 \cup B_2 \cup C \cup D)$	knowing masking effects				one fault
$\alpha(B_1 \cup B_2 \cup C \cup D)$	$\alpha(A \cup B_1 \cup B_2 \cup C)$	$\alpha(A \cup B_1 \cup B_2 \cup C)$	$\alpha(A \cup B_1 \cup B_2 \cup C)$	$\alpha(A \cup B_1 \cup B_2 \cup C)$	$\alpha(A \cup B_1 \cup B_2 \cup C)$
(1,1,-,-,0)	(1,1,1,-,0)	(1,1,1,-,0)	(1,1,1,-,0)	(1,-,1,-,0)	(1,-,1,-,0)
(1,-,1,1,-,0)	(1,-,1,1,-,0)	(1,-,1,1,-,0)	(1,-,1,1,-,0)	(0,0,-,-,0)	(0,0,-,-,0)
(0,0,0,0,-,0)	(0,0,0,-,-,0)	(0,0,0,-,-,0)	(0,0,0,-,-,0)	(0,-,-,-,0,0)	(0,-,-,-,0,0)
(0,-,1,1,-,1)	(0,0,-,-,0,0)	(0,0,-,-,0,0)	(0,0,-,-,0,0)	(-,-,1,-,0,0)	(-,-,1,-,0,0)
	(-,-,1,1,0,0)	(-,-,1,1,0,0)	(-,-,1,1,0,0)	(-,-,1,-,0,0)	(-,-,1,-,0,0)
	(0,-,1,1,1,1)	(0,-,1,1,1,1)	(0,-,1,1,1,1)	(-,-,0,-,0,-,0)	(-,-,0,-,0,-,0)
				(-,-,1,1,1,1)	(-,-,1,1,1,1)
				(1,-,1,1,1,-)	(1,-,1,1,1,-)
				(-,-,0,1,1,1,-)	(-,-,0,1,1,1,-)
transformation					
$c_m$	$c_{origin}$	$c_{new}$	$c_m$	$c_{origin}$	$c_{new}$
$c_m = c_{origin} \rightarrow c_{new} < c_m$	(1,-,1,1,-,0)	(1,-,1,1,-,0)	(1,-,1,1,-,0)	(1,-,1,1,-,0)	(1,-,1,1,-,0)
$c_m < c_{origin} \rightarrow c_{new} < c_m$	(1,1,-,-,-,0)	(1,1,1,-,-,0)	(1,1,-,-,-,0)	(1,1,1,-,-,0)	(1,1,1,-,-,0)
$c_{origin} \rightarrow c_{new}$ irrele	(0,-,1,1,1,1)	(0,-,1,1,1,1)	(0,-,1,1,1,1)	(-,-,1,1,1,1)	*
$c_{origin} < c_m \rightarrow c_{new} < c_m$	(0,0,0,0,-,0)	(0,0,0,-,-,0)	(0,0,0,-,-,0)	(0,0,0,-,-,0)	(0,0,0,-,-,0)
$irrele \rightarrow c_{new} < c_m$	*	(0,0,-,-,0,0)	(0,0,-,-,0,0)	(0,0,-,-,0,0)	(0,0,0,-,-,0)
$\rightarrow c_{new}$ irrele	*	(-,-,0,1,1,0,0)	(-,-,0,1,1,0,0)	(-,-,0,1,1,0,0)	*
$c_{new} < c_m$	*	*	(-,-,0,-,0,-,0)	(-,-,0,-,0,-,0)	(0,0,0,0,-,0)
$c_{new} < c_m$	*	*	(1,-,1,1,1,-)	(1,-,1,1,1,-)	*

We take an example to illustrate this type of transformation, which is depicted in Table XIV. Similar to our previous strategy, we omit the samples that belong to the identical transformations.

We note that in addition to the transformations that correspond to each directed line that is depicted in Figure 6, there is one more transformation that can appear in this strategy, which can make some  $c_{origin}$  removed from the newly minimal schemas, i.e.,  $c_{new}$ :  $S.t.: c_{new} = c_{origin}$  or  $c_{origin} < c_{new}$ . For the example of the Table XIV example, in the last row we used a formula  $c_{origin}$  ignored to represent this condition, with the mark \* in the  $c_{new}$  indicating that the  $c_{origin}$  is irrelevant to all the  $c_{new}$ . In this row, we can find for the schema  $c_{origin} = (1,1,0,0,1,-)$ , which is identical to the one in the actual MFS; there exists no  $c_{new}$  which is identical to or is the parent-schema of this schema. Consequently, in this condition, this strategy may ignore some actual MFS compared with knowing masking effects.

In fact, besides this special case that may result in make the FCI approach ignoring some actual MFS, there exists some other cases that can also achieve the same effect; for example, when

the  $c_{new}$  is the only schema that is related to  $c_{origin}$ , (related means not irrelevant, and in this case it is either identical to or the parent-schema). And the corresponding parent-schema

$c_{origin}$  is the only schema which is related to one actual MFS  $c_m$ . Then, if the  $c_{new}$  is irrelevant to all the actual MFS, we will ignore the actual MFS  $c_m$ . This ignored event

is caused by the  $c_{new}$  growing into the irrelevant schemas, which can also be appeared in the strategy regard as one fault. However, the aforementioned cause of ignored-the

*Origin* is

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Table XIV. Example the influence of distinguish faults for FCI approach

A	B <sub>1</sub>	C	B <sub>2</sub>	D
(0,0,0,1,1,0)	∅	(0,0,0,1,1,0)	(0,0,1,1,1,0)	(0,1,1,0,0,0)
(0,0,1,1,0,0)	(0,0,0,0,1,0)	(1,1,0,1,0,0)	(1,1,0,1,0,0)	(0,1,1,0,1,0)
(0,0,1,0,1,0)	(0,0,0,1,0,0)	(1,0,1,1,0,1)	(0,0,1,1,0,1)	(0,1,1,1,0,0)
(0,0,1,0,0,0)	(1,1,1,1,1,0)	(0,0,1,1,1,1)	(0,0,1,1,1,1)	(0,1,1,1,1,0)
(1,1,0,0,0,0)	(1,1,0,0,1,0)	(1,1,0,0,1,1)	(1,1,0,0,1,1)	(1,1,1,1,1,1)
(0,0,1,1,0,1)	(1,1,0,1,1,0)	(0,1,0,0,1,1)	(0,1,0,0,1,1)	(0,1,1,1,1,1)
	(1,1,1,0,0,0)	(1,0,1,0,1,1)	(1,0,1,0,1,1)	(1,1,1,1,0,1)
	(1,1,1,1,0,0)			(1,0,0,1,1,1)
	(1,1,1,0,1,0)			
	(1,0,1,1,1,1)			
	(0,0,0,0,1,1)			
	(1,0,0,0,1,1)			
actual MFS α(B <sub>1</sub> B <sub>2</sub> C D) (0,-,1,1,-)	knowing masking effects α(A B <sub>1</sub> B <sub>2</sub> C) (1,1,-,-,0)	distinguish faults α(A B <sub>1</sub> C) (0,0,0,-,0)		
(1,1,-,1,-,0)	(0,0,-,-,-,0)	(0,0,-,-,0,0)		
(-, -,0,0,1,1)	(-,0,1,1,-,1)	(0,0,-,0,-,0)		
(0,0,0,-,0,0)	(0,0,1,1,-,-)	(1,1,1,-,-,0)		
(0,0,0,0,-,0)	(0,0,0,0,1,-)	(1,1,-,-,1,0)		
(1,0,-,-,1,1)	(1,1,0,0,1,-)	(1,1,-,0,-,0)		
(1,1,0,0,1,-)	(1,0,1,-,1,1)	(0,0,1,1,0,-)		
(-,1,1,-,-,0)	(1,0,-,0,1,1)	(1,0,1,1,1,1)		
(-, -,1,1,1,1)	(-, -,0,0,1,1)	(-,0,0,0,1,1)		
(1,1,-,-,1,0)		(0,0,0,0,1,-)		
(-,1,1,1,1,-)				
(1,1,1,1,-,-)				
(1,-,1,1,-,1)				
(0,0,0,0,1,-)				
transformation	C <sub>m</sub>	C <sub>origin</sub>	C <sub>new</sub>	C <sub>m'</sub>
C <sub>m</sub> = C <sub>origin</sub> → C <sub>m</sub> < C <sub>new</sub>	(-, -,0,0,1,1)	(-, -,0,0,1,1)	(-,0,0,0,1,1)	(-, -,0,0,1,1)
C <sub>m</sub> < C <sub>origin</sub> → C <sub>m</sub> < C <sub>new</sub>	(1,0,-,-,1,1)	(1,0,1,-,1,1)	((1,0,1,1,1,1))	((1,0,-,-,1,1))
C <sub>origin</sub> < C <sub>m</sub> → C <sub>new</sub> irrele	(1,1,-,1,-,0)	(1,1,-,-,0,0)	(1,1,-,0,-,0)	
C <sub>origin</sub> < C <sub>m</sub> → C <sub>new</sub> < C <sub>m</sub>	(0,0,0,0,-,0)	(0,0,-,-,-,0)	(0,0,0,-,-,0)	(0,0,0,0,-,0)
C <sub>origin</sub> < C <sub>m</sub> → C <sub>m</sub> < C <sub>new</sub>	(1,1,-,1,-,0)	(1,1,-,-,0,0)	(1,1,1,-,-,0)	(-,1,1,-,-,0)
C <sub>origin</sub> < C <sub>m</sub> → C <sub>m</sub> = C <sub>new</sub>	(1,1,-,-,1,0)	(1,1,-,-,0,0)	(1,1,-,-,1,0)	(1,1,-,-,1,0)
C <sub>origin</sub> irrele → C <sub>m</sub> < C <sub>new</sub>	*	(-,0,1,1,-,1)	(1,0,1,1,1,1)	(1,-,1,1,-,1)
C <sub>origin</sub> irrele → C <sub>new</sub> irrele	*	(0,0,1,1,-,-)	(0,0,1,1,0,-)	*
C <sub>origin</sub> ignored	(1,1,0,0,1,-)	(1,1,0,0,1,-)	*	*

removed from the newly minimal schemas can only happens in the strategy distinguish faults.

#### 4.3. Summary of the masking effects on the FCI approach

From the analysis of the formal model, we can learn that masking effects do influence the FCI approaches, and even worse more, both the strategies regard as one fault and distinguish faults strategy are harmful. Specifically, which specifically the former compares the knowing masking effects have a large possibility of getting that get more sub-schemas of the actual MFS and getting more schemas which are irrelevant to the MFS, while the latter may get more parent schemas of the MFS and can also get more irrelevant MFS. Further, both the two strategies can ignored the actual MFS and the distinguish faults strategy is more likely to ignore the MFS than the regard as one fault strategy.

Note that our discussion is based on that SUT using is a deterministic software, i.e., the random failing information of a test case will be ignored. The non-deterministic problem results in a more will complex our test scenario, which will not be discussed in this paper.

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## 5. TEST CASE REPLACING STRATEGY

The main reason why the FCI approach fails to properly work is that we cannot determine the areas  $B_2$  and  $B_3$ , i.e., if the test case under test triggers other faults which are different from the current one, we cannot figure out whether this test case will trigger the current expected fault as the masking effects may prevent that. So in order to limit the impact of this effect on the FCI approach, we need to reduce the number of test cases that trigger other faults as much as possible.

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In the exhaustive testing, as all the test cases will be used to identify the MFS, there is no room left to improve the performance without fixing the other faults and re-executing all the test cases. However, when you just needing to select part of all the whole test cases to identify the MFS, which is howas the traditional FCI approach works, we can adjust the test cases we need to use by selecting the proper ones, thereby limiting so that we can limit the size of  $T(mask_{F_m})$  so that it is to be as small as possible.

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### 5.1. Replacing test cases that triggering an unexpected fault

The basic idea is to pick the test cases that trigger other faults and generate newly test cases to replace them. These regenerated test cases should either pass in the execution or trigger  $F_m$ . The replacement must satisfy the condition that the newly generated ones will not negatively influence the original identifying process.

Commonly, when we replace the test case that triggers an unexpected fault with a new test case, we should keep some part in the original test case. We call this part theas fixed part, and mutate the other part with different values from the original one. For example, if a test case (1,1,1,1) triggered an unexpected fault, and the fixed part is (-,-,1,1), which then we can replace it with a test case (0,0,1,1) which may either pass or trigger an expected fault.

The fixed part can varies for different FCI approaches, e.g., for the OFOT algorithm, the factors are the fixed part is the factors except for the one that needs to be validated, even if whether it is the component of the MFS, while for the FIC BS, we will fix the factors that should not be mutated for of the test case in the next iteration of the FIC BS process.

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We note it is noted that this replacement may need to be executed multiple times for one fixed part as we could not always find a test case that by coincidence satisfied our requirements. Our previous work just randomly choose test cases until one was found that find one satisfied the test case. That brute method may be simple and really works, but also it may require trying need to try too many times to get the satisfied one. So to handle this problem and reduce the cost, we augmented our previous approach by with computing the strength of the test case with the other faults, and then we will selected the one test case from a group of candidate test cases that has the least strength that is related to the other faults.

To explain the strength notation, we need first to introduce the strength with which that a factor is related to a particular fault. We use  $all(o)$  to represent the number of executed test cases that contain this factor, and  $m(o)$  to indicate the number of test cases that trigger the fault  $F_m$  and contain this factor. Then, a the strength that a factor is related to a

particular fault, i.e.,  $S(o; F_m)$ , is  $\frac{m(o)}{all(o)+1}$ . This heuristic formula is based on the idea that if a factor frequently appears in the test cases that trigger the particular fault, then it is more likely to be the inducing factor that triggers this type of fault. We plus use 1 in the denominator for two facts: 1. avoid the division by zero when the factor is has never

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| appeareds before, and 2. reduce the bias when a factor rarely appears in the test set but by coincidence appears in a failing test case with a particular fault.

| With this ~~factor strength~~ ~~of the factor~~, we then define ~~that~~ the *strength* ~~of~~ a test case  $f$  is related to a particular fault  $F_m$  as:

$$S(f; F_m) = \frac{1}{\sum_{o \in F_m} 1} S(o; F_m)$$

In this formula,  $k$  is the number of factors in the test case  $f$ ,  $o$  is the specific factor in  $f$ . This formula computes the average *strength* of all the factors in the test case as the *strength* for this test case that is related to a particular fault. For a test case that is selected to be tested, we want that the ability of that case to trigger another fault to be as small as possible. In practice, one test case can have different related *strength* to different faults, so we can not always find a test case that has the least relating *strength* to all the faults when comparing to other test cases. With this fact in mind, our target changes to find a test case for which the maximal *strength* it is of the related fault among other faults is the least compared to other test cases. Formally, we should choose a test case  $f$ , s.t.,

$$\min_{f \in R} \max_{m \leq L, m \neq n} S(f; F_m) \quad (\text{EQ1})$$

In this formula,  $L$  is the number of all the faults, and  $n$  is the current analysed fault.  $R$  is the set of all the possible test cases that contain the *fixed* part except those ones that

have been tested. Obviously  $|R| = \prod_{i \in \text{fixed}(v_i)} |t|$  where  $t$  contains the fixed part &  $t$  is tested.

We can further resolve this problem. Consider the test case we get that satisfied the EQ1. Without loss of generality, we assume that the fault  $F_k$ ;  $k \neq n$  is the fault with which the test case  $f$  has the maximal related *strength* compared to the other faults. Then, a natural property for  $f$  is that any other test case  $f'$  which satisfies that fault  $F_k$  is the maximal related fault for this test case and must have  $S(f; F_k) \leq S(f'; F_k)$ . Formally, to get such a test case is to solve the following formula:

$$\begin{aligned} \min \quad & S(f; F_k) \\ \text{s.t.} \quad & f \in R \end{aligned} \quad (\text{EQ2})$$

$$S(f; F_k) > S(f; F_i); \quad 1 \leq i \leq L \text{ \& } i \neq k; n$$

With this formula, to solve the EQ1, we just need to find the particular fault  $F_k$ , such that the related *strength* between the test case  $f$  satisfies the EQ2, and this fault is the smallest than all other faults. Formally, we need to find:-

$$\min S(f; F_k) \text{ (EQ3) s.t. } 1 \leq k \leq L \text{ \& } k \neq n$$

$$f; F_k \text{ satisfies EQ2}$$

According to the EQ3, the problem that to get such a test case lies in solving the EQ2, because if EQ2 is solved, we just need to rank the one that has the minimal value from the solutions to EQ2. As to EQ2, it can be formulated as an 0-1 integer linear programming (ILP) problem. Assume the SUT we test has  $K$  factors, in which the  $i$ th factor has  $V_i$  values can it can take from. And the SUT has  $L$  faults. We then define the variable  $x_{ij}$  as:

$$x_{ij} = \begin{cases} 1 & \text{the } i\text{th factor of the test case take the } j\text{th value for that factor} \\ 0 & \text{otherwise} \end{cases}$$

We then take  $o_{mij}$  to be the related *strength* between the  $j$ th value of the  $i$ th factor of the SUT and the fault  $F_m$ . And we use a set  $R$  of factors with its values to define the fixed part in the test case we should not change, i.e.,  $R =$

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$\{(i; j) | i \text{ is the fixed factor in the test case; } j \text{ is the corresponding value}\}$ . As we can generate redundant test cases, so we keep a set of test cases  $T_{executed}$  to guide to generate different test cases. Then the EQ2 can be detailed as in the following ILP:

$$\begin{aligned}
 \min \quad & \frac{1}{K} \sum_{i=0}^{K-1} \sum_{j=0}^{V_i-1} x_{ij} \quad (EQ4) \\
 \text{s.t.} \quad & 0 \leq x_{ij} \leq 1 \quad i = 0::K-1; j = 0; ::V_i-1 \quad (1) \\
 & x_{ij} \in \mathbb{Z} \quad i = 0::K-1; j = 0; ::V_i-1 \quad (2) \\
 & \sum_{j=0}^{V_i-1} x_{ij} = 1 \quad i = 0::K-1 \quad (3) \\
 & \sum_{i=0}^{K-1} x_{ij} = 1 \quad (i; j) \in R \quad (4) \\
 & \sum_{i=0}^{K-1} \sum_{j=0}^{V_i-1} (o_{mij} - o_{m'_{ij}}) x_{ij} \geq 0 \quad 1 \leq m' = m \leq L \quad (5) \\
 & \sum_{(i; j) \in T_{existed}} x_{ij} < K \quad (6)
 \end{aligned}$$

In this formula, the constraints (1) and (2) indicate that the variable  $x_{ij}$  is a 0-1 integer. Constraint (3) indicates that a factor in one test case can only take one value. Constraint (4) indicates the test case should not change values of the fixed part. Constraint (5) indicates that the related strength between Fault  $F_m$  and the test case is greater maximal than the others. Constraint (6) indicates the test cases generated should not be the same as the test cases in  $T_{existed}$ .

As we have formulated the problem into a 0-1 integer programming problem, we just need to utilize an ILP solver to solve this formula. In this paper, we use the solver introduced in [Berkelaar *et al.* 2004], which is a mixed Integer Linear Programming (MILP) solver that can handle satisfaction and optimization problems.

The complete process of replacing a test case with a new one while keeping some fixed part is depicted in Algorithm 1:

The inputs for this algorithm consists of the fault type. We currently focus on  $-F_m$ , the fixed part of which we want to keep from the original test case –  $S_{fixed}$ , the values sets that each factor can take from respectively –  $Param$  and the set of matrix  $o_1; \dots; o_L$ , for any element in which, say  $o_m$ , is recorded the related strength between each specific factor with each value and the fault  $F_m$ , i.e.,  $o_m = \{o_{mij} | 0 \leq i \leq K-1; 0 \leq j \leq V_i\}$ . The output of this algorithm is a test case  $t_{new}$  which either triggers the expected  $F_m$  or passes.

This algorithm is an outer loop (lines 1 - 19) containing two parts:

The first part (lines 2 - 9) generates a new test case which is supposed to be least likely to trigger faults different from  $F_m$ . The basic idea for this part is to search each fault different from  $F_m$  (line 3) and find the best test case that has the least related strength with other faults. In detail, for each fault we set up an ILP solver (line 4) and use it to get an optimal test case for that fault according to EQ4 (line 5). We compare the optimal value for each fault, and choose the one has less strength related to other faults (lines 6 - 9).

The second part is to check whether the newly generated test case is as expected

| (lines 10 - 16). We first execute the SUT under the newly generated test case (line 10) and update the related strength matrix ( $o_1::o_L$ ) for each factor that is involved in this

**ALGORITHM 1:** Replacing test cases triggering unexpected faults

**Input:** fault type  $F_m$ , fixed part  $s_{fixed}$ , values set that each option can take  $Param$ , the related strength matrix  $o_1 \dots o_L$

**Output:**  $t_{new}$  the regenerate test case,  $t$  the frequency number

```

1 while not MeetEndCriteria() do
2   optimal MAX;  $t_{new}$  null;
3   forall the  $F_k \in F_1 \dots F_m; F_{m+1} \dots F_L$  do
4     solver setup( $s_{fixed}$ ;  $Param$ ;  $F_m$ ;  $o_1 \dots o_L$ );
5     ( $optimal$ ;  $t_{new}$ ) solver.getOptimalTest();
6     if  $optimal < optimal$  then
7        $t_{new} = t_{new}$ ;
8     end
9   end
10  result execute( $t_{new}$ );
11  updateRelatedStrengthMatrix( $t_{new}$ );
12  if result == PASS or result ==  $F_m$  then
13    return  $t_{new}$ ;
14  else
15    continue;
16  end
17 end
18 return null

```

newly generated test case (line 11). We then check the executed result: if either the test case passes or triggers the same fault –  $F_m$ , we will get a satisfied test case (line 12), and we will directly return this test case (line 13). Otherwise, we will repeat the process, i.e., generate a new test case and check again (line 14 - 15).

We note that this algorithm has another exit, besides we find an expected test case (line 12), which is when the function *MeetEndCriteria()* returns true (line 1). We didn't explicitly show what the function *MeetEndCriteria()* is like, because this is dependent on the computing resource and how accurate you want the identifying result to be. In detail, if you want to get a high quality result and you have enough computing resource, you can try many times to get the expected test case; otherwise, a relatively small number of attempts is recommended.

In this paper, we just set 3 as the greatest number of biggest repeated times for this function. When it ends with *MeetEndCriteria()* is true, we will return null (line 18), which means we cannot find an expected test case.

## 5.2. A case study using the replacement strategy

Suppose we have to test a system with eight parameters, each of which has three options. And when we execute the test case  $T_0 = (0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0)$ , a failure  $e_1$  is triggered. Next, we will use the FCI approach – FIC BS [Zhang and Zhang 2011] with replacement strategy to identify the MFS for the  $e_1$ . Furthermore, there are two more potential faults,  $e_2$  and  $e_3$ , that may be triggered during the testing, which will mask the desired fault  $e_1$ . The process is shown in Figure 7. In this figure, there are two main columns: in this figure, the left main column indicates the executed test cases during testing as well as their executed results, and each executed test case corresponds to a specific label  $T_1 - T_8$  at the left. The right main column lists the related strength matrix when we come with a test case triggered  $e_2$  or  $e_3$ . In detail, the matrix records the related strength between each factor (columns  $O_1 - O_8$ ) for each value it can take (column  $v$ ) with the unexpected fault (column  $F$ ). The executed test case, which is in bold, indicates the one that triggers the other faults and should be replaced in the next iteration.

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Table XV. The number of test cases each FCI approach needed to identify the MFS

Method	number of test cases to identify MFS
Charles ELA	depends on the covering array
Martinez with safe value [Martínez et al. 2008; 2009]	$O(d^c + d \log k + \log^c k)$
Martínez without safe values [Martínez et al. 2008; 2009]	$O(d \log k + \log^c k)$
Martínez' ELA [Martínez et al. 2008; 2009]	$O(ds \log k)$
Shi SOFOT [Shi et al. 2005]	$O(k)$
Nie OFOT [Nie and Leung 2014]	$O(k \times d)$
Yilmaz classification tree	depends on the covering array
FIC [Zhang and Zhang 2011]	$O(k)$
FIC BS [Zhang and Zhang 2011]	$O(t(\log k + 1) + 1)$
Ghandehari's suspicious based [Ghandehari et al. 2012]	depends on the number and size of MFS
TRT [Niu et al. 2013]	$O(d \times t \times \log k + t^u)$

From Figure 7, for the test case that triggered  $e2 - (2 \ 1 \ 1 \ 0 \ 0 \ 0 \ 0)$  (in this case, the fixed part of the test case is  $(- \ - \ - \ 0 \ 0 \ 0 \ 0)$ , in which the last four factors are the same as the original test case  $T_0$ ), we generate the related matrix in the left. Each element in

this matrix is computed as the  $\frac{m(o)}{all(o)+1}$ . For example, for the  $O7$  factor with value 0, we can find two test cases that contain this element, i.e.,  $T_0$  and  $T_1$ , so the  $all(o)$  is 2. And only one test case triggers the fault  $e2$ , which means  $m(o) = 1$ . So the final related strength between this factor with  $e2$  is  $\frac{1}{2+1} = 0.33$ . All the related strength with  $e3$  is labeled with a short slash as there is no test case triggering this fault in this iteration. After this matrix has been determined, we can obtain an optimal test case with the ILP solver, which is  $T_1 - (1 \ 2 \ 2 \ 2 \ 0 \ 0 \ 0)$ , with its related strength 0.167, which is smaller than that of the others.

This replace process triggered each time a new test case that triggered another fault, and until we finally get the MFS. Some times we could not find a satisfied replacing test case in just one trial like  $T_1$  to  $T_1$ . When this happened, we will need to repeat searching the proper test case we desired, e.g., For example, for  $T_4$ , which triggered  $e3$ , we tried three times—  $T_4$ ;  $T_4$ ;  $T_4$  to finally get a satisfied one  $T_4$  which passes the testing. It is noted that the matrix continues to change with the test case generated and executed so that we can adaptively find an optimal one in the current process.

### 5.3. Complexity analysis

This complexity relies on two facts: the number of test cases that triggered other faults which need to be replaced, and the number of test cases that need to be tried to generate a non-masking-effects test case. The complexity is the product of these two facts.

The first fact is comparable to the extra test cases that are needed to identify the MFS, and this number varies in different FCI approaches. Table XV lists the number of test cases that each algorithm needed to get the MFS. In this table,  $d$  indicates the number of MFS in the SUT.  $k$  means the number of the parameters of the SUT.  $t$  is the number of MFS factors of the MFS in the SUT.  $c$  is an upper bond, and satisfies,  $d \leq 2^c$ .  $\log \log k$ .  $v$  is the number of values one parameter can take.

It must be noted that each algorithm may be limited to some restrictions to identify the result, details of which are shown in [Zhang and Zhang 2011].

To get the magnitude of the second fact, we need to figure out the possibility of that a test case that could trigger other fault. The first thing we need to consider is the fixed part, as the additional generated test case should somehow contain this part. As we have mentioned before, we can in fact generate  $(v-1)^{k-p}$  ( $p$  is the number of factors in the fixed part) possible test cases that contain the fixed part. Apart from the one that

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needs to be replaced, there remain  $(v - 1)^{k-p} - 1$ , which indicates the complexity is  $O((v - 1)^{k-p} - 1)$ . However, to avoid the exponential computational complexity, ~~we~~ in this algorithm ~~we~~ use ~~thea~~ method *MeetEndCriteria()* (line 1) function to end the algorithm

Test Cases & output			Related strength matrix									
			v	F	O1	O2	O3	O4	O5	O6	O7	O8
T <sub>0</sub>	0 0 0 0 0 0 0	E1										
T <sub>1</sub>	2 1 1 1 0 0 0	E2										
T <sub>1</sub> '	1 2 2 0 0 0 0	PASS										
T <sub>2</sub>	1 2 0 0 0 0 0	PASS										
T <sub>3</sub>	1 0 0 0 0 0 0	PASS										
T <sub>4</sub>	0 2 2 2 2 1 1 2	E3										
T <sub>4</sub> '	0 2 1 2 1 2 2 1	E2										
T <sub>4</sub> ''	0 2 2 1 2 2 2 2	E3										
T <sub>4</sub> '''	0 1 2 2 1 1 1 1	PASS										
T <sub>5</sub>	0 2 2 2 1 0 0 0	PASS										
T <sub>6</sub>	0 2 2 0 0 0 0 0	PASS										
T <sub>7</sub>	0 2 0 0 0 0 0 0	PASS										
T <sub>8</sub>	0 0 2 2 1 1 1 1	E1										

	e2	0	0	0	0	0.33	0.33	0.33	0.33
	e3	-	-	-	-	-	-	-	-
1	e2	0	0.5	0.5	0.5	0	0	0	0
	e3	-	-	-	-	-	-	-	-
2	e2	0.5	0	0	0	0	0	0	0
	e3	-	-	-	-	-	-	-	-

	e2	0	0	0	0	0.17	0.17	0.17	0.17
	e3	0.33	0	0	0	0	0	0	0
1	e2	0	0.5	0.5	0.5	0	0	0	0
	e3	0	0	0	0	0	0.5	0.5	0
2	e2	0.5	0	0	0	0	0	0	0
	e3	0	0.25	0.33	0.33	0.5	0	0	0.5

	e2	0.25	0	0	0	0.17	0.17	0.17	0.17
	e3	0.25	0	0	0	0	0	0	0
1	e2	0	0.5	0.67	0.5	0.5	0	0	0.5
	e3	0	0	0	0	0	0.5	0.5	0
2	e2	0.5	0.2	0	0.25	0	0.5	0.5	0
	e3	0	0.2	0.33	0.25	0.5	0	0	0.5

	e2	0.2	0	0	0	0.17	0.17	0.17	0.17
	e3	0.4	0	0	0	0	0	0	0
1	e2	0	0.5	0.67	0.33	0.5	0	0	0.5
	e3	0	0	0	0.33	0	0.5	0.5	0
2	e2	0.5	0.17	0	0.25	0	0.33	0.33	0
	e3	0	0.33	0.5	0.25	0.67	0.33	0.33	0.67

Fig. 7. A case study using our approach

when the trying times is over a prior given constant, say  $N$ , so the final complexity for the second part is  $O(\min(N; (\nu - 1)^{k-p} - 1))$ .

We note it is noted that exponential factor  $k - p$  directly affects the complexity of the second factor. The greater  $p$  is, the less test cases that can be generated. For a different approach,  $p$  is different. As for OFOT,  $p$  is a fixed number, which is  $k - 1$ . This is the minimal number of the test cases we need to use. While for the non-adaptive, as the fixed part is the coverage, we list them as  $t$ . We have listed all of them in Table XVI. It is noted that the Martinez without safe values has no such complexity, this is because this approach works when  $\nu = 2$ , and this will result in that we will not have other test cases to be replaced if we test a fixed part when triggering other faults.



Table XVI. The complexity of the second part

Method	Fixed part
Charles ELA	$O(\min(N; (v-1)^{K^{\mu}} - 1))$
Martinez with safe value [Martínez et al. 2008; 2009]	$O(\min(N; (v-1) - 1)) - O(\min(N; (v-1)^{K^{-1}} - 1))$
Martinez without safe values [Martínez et al. 2008; 2009]	$-$
Martinez' ELA [Martínez et al. 2008; 2009]	$O(\min(N; (v-1)^{K^{\mu}} - 1))$
Shi OFOT [Shi et al. 2005]	$O(\min(N; (v-1) - 1))$
Nie OFOT [Nie and Leung 2011]	$O(\min(N; (v-1) - 1))$
Yilmaz classification tree	$O(\min(N; (v-1)^{K^{\mu}} - 1))$
FIC [Zhang and Zhang 2011]	$O(\min(N; (v-1) - 1)) - O(\min(N; (v-1)^{K^{-1}} - 1))$
FIC BS [Zhang and Zhang 2011]	$O(\min(N; (v-1) - 1)) - O(\min(N; (v-1)^{K^{-1}} - 1))$
Ghandehari's suspicious based [Ghandehari et al. 2012]	$O(\min(N; (v-1)^{K^{\mu}} - 1))$
TRT [Niu et al. 2013]	$O(\min(N; (v-1) - 1)) - O(\min(N; (v-1)^{K^{-1}} - 1))$

Table XVII. Software under survey

software	versions	LOC	classes	bug pairs
HSQLDB	2.0rc8	139425	495	#981 & #1005
	2.2.5	156066	508	#1173 & #1179
	2.2.9	162784	525	#1286 & #1280
JFlex	1.4.1	10040	58	#87 & #80
	1.4.2	10745	61	#98 & #93

## 6. EMPIRICAL STUDIES

To investigate the impact of masking effects for FCI approaches in real software testing scenarios and to evaluate the performance that how well our approach handles this effect, we conducted several empirical studies which we discuss in this section. Each one of the studies focuses on addressing one particular issue/problem, as follows which are listed as following:

**Q1:** Do masking effects exist in real software that when it contains multiple faults?

**Q2:** How well does much do our approach performs compared to with traditional approaches?

**Q3:** Is the ILP-based test case searching technique efficient compared to random selection? with randomly selecting?

**Q4:** Compared to with another existed masking effects handling approaches work – the FDA-CIT [Yilmaz et al. 2013], does our new approach have any advantages?

### 6.1. The existence and characteristics of masking effects

In the first study, we surveyed two open-source kinds of software to gain an insight into the existence of multiple faults and their effects. The software under study were are: HSQLDB and JFlex. The first is a database management software written in pure Java, and the second is a lexical analyser generator. Each of them contains different versions. Each is All the two subjects are highly configurable so that the options and their combinations can influence their behaviour. Additionally, they all have a developers' community so that we can easily obtain the real bugs reported in the bug tracker forum. Table XVII lists the program, the number of versions we surveyed, number of lines of uncommented code, number of classes in the project, and the bug's id of for each of the software we studied.

**6.1.1. Study setup.** We first looked through the bug tracker forum of each software and focused on the bugs which are caused by the options combination. For each such bug, we will derive its MFS by analysing the bug description report and the attached test file which can reproduce the bug. For example, through analysing the source code of the test file of bug

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#981 for HSQLDB, we found the failure-inducing combinations for

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<sup>3</sup><http://sourceforge.net/projects/bugs> <http://sourceforge.net/projects/bugs>

ACM Transactions on Embedded Computing Systems, Vol. 9, No. 4, Article 39, Publication date: March 2010.

this bug areis: (*preparestatement*, *placeholder*, *Long string*). These three factors together form the condition that triggers the bug on which the bug will be triggered. These analysed results will be later regarded as the “prior MFS” later.

We further built the testing scenario for each version of the software listed in Table XVII. The testing scenario is properly constructed so that we can reproduce different faults bythrough controlling the inputs to theat test file. For each particular version of the software, the source code of the testing file as well as other detailed experiment information is available at <https://code.google.com/p/merging-bug-file>.

Next, we built the input model which consists of the options related to the failure-inducing combinations and additional noise options. The detailed model information is in Tables XVIII and XIX for HSQLDB and JFlex, respectively. Each table is organised into four groups: (1) “common options”, which lists the options as well as their values under which every version of this software can be tested; (2) “common bBoolean options”, which lists additional common options whose data type is bBoolean; (3) “specific options”, under which only the specific version of that software can be tested; and (4) “configure space”, which depicts the input model for each version of the software, the input model is presented in the abbreviated form  $\#values^{\#number\ of\ parameters} \times \dots$ , e.g.,  $2^9 \times 3^2 \times 4^1$  indicates the software has ve 9 parameters that can take 2 values, 2 parameters that can take 3 values, and only one factor that can take 4 values.

Table XVIII. Input model of HSQLDB

common options		values
Server Type		server, webserver, inprocess
existed form		mem, file
resultSetTypes		forwad, insensitive, sensitive
resultSetConcurrencys		read_only, updatable
resultSetHoldabilitys		hold, close
StatementType		statement, prepared
common <u>b</u> Boolean options		
sql.enforce strict size, sql.enforce.names, sql.enforce refs		
versions	specific options	values
2.0rc8	more	true, false
	placeholder	true, false
	cursorAction	next, previous, first, last
2.2.5	multiple	one, multi, default
	placeholder	true, false
2.2.9	duplicate	dup, single, default
	default-commit	true, false
versions	Config space	
2.0rc8	$2^9 \times 3^2 \times 4^1$	
2.2.5	$2^8 \times 3^3$	
2.2.9	$2^8 \times 3^3$	

We then generated the exhaustive test suite consisting of all the possible combinations of these options, and under each of them, we executed the prepared testing file. We recorded the output of each test case to observe whether there wereare test cases containing prior MFS that did but do not produce the corresponding bug.

6.1.2. *Results and discussion.* Table XX lists the results of our survey. Column “all tests” give the total number of test cases we executed, Column “failure” indicate the number of test cases that failed during testing, and Ccolumn “masking” indicates the number of test cases which triggered the masking effect.

We observed that for each version of the software under analysis that we listed in the Table XX, the test cases with masking effects do exist, i.e., test cases containing MFS did not trigger the corresponding bug. In effect, there areis about 768 out of 4608 test

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Table XIX. Input model of JFlex

common options		values
generation		switch, table, pack
charset		default, 7bit, 8bit, 16bit
common boolean options		
public, apiprivate, cup, caseless, char, line, column, notunix, yyeof		
versions	specific options	values
1.4.1	hasReturn	has, non, default
	normal	true, false
1.4.2	lookAhead	one, multi, default
	type	true, false
	standalone	true, false
versions	Config space	
1.4.1	$2^{11} \times 3^2 \times 4^1$	
1.4.2	$2 \times 3 \times 4$	

Table XX. Number of faults and their masking effects

software	versions	all tests	failure	masking
HSQldb	2cr8	18432	4608	768
-	2.2.5	6912	3456	576
-	2.2.9	6912	3456	1728
JFlex	1.4.1	36864	24576	6144
-	1.4.2	73728	36864	6144

cases (16.7%) in hsqldb with 2cr8 version. This rate is about 16.7%, 50%, 25%, and 16.7%, respectively, for the remaining software versions, which is not trivial.

So the answer to Q1 is that in practice, when SUT have multiple faults, the masking effects do exist widely in the test cases.

## 6.2. Comparing our approach with traditional algorithms

In the second study, our aim was to compare the performance of our approach to traditional approaches in identifying the MFS under the impact of masking effects. To conduct this study, we needed to respectively apply the our approach and traditional algorithms to identifying MFS in a group of software and evaluate their identifying results. The five prepared versions of software in Table XVII used as test objects as testing subjects is far from a general evaluation of such objects. However, to construct such real testing scenarios is time-consuming as we must need to carefully study the tutorial of that software as well as the bug tracker report. So in order to give a desirable result based on more testing objects, we then synthesize a number of such testing scenarios of which the characterizations, such as the number of factors, the number of faults, and the possible masking effects, are similar to that of the real software. In detail, we set the number of parameters  $k$  of the SUT to a ranged from 8 to 30. We limited the scale of the SUT to a relatively small size because we needed to exhaustively execute each possible test case of the SUT to select the failing test cases which we and then fed into them to the FCI approach. We then randomly choose 10 such SUTs, and for each SUT we injected 2 to 5 different MFS into it, which that can mask each other. The degree of the MFS we injected are ranged from 1 to 6.

Above all, Table XXI lists the testing model for both the real and synthesizing testing scenario. In this table, the column 'software' indicates the SUT under test. For the real SUT, we label it with the form 'name + version', while for the synthesizing ones, we label them as 'synthes+ id'. The column 'Model' presents the model of the input space for that software. The last column shows the MFS as well as their masking sequence for each testing object. The MFS is presented in an abbreviated form  $\{index\#value\}$ , e.g.,  $(5_1; 6_0; 7_0)$  actually means  $(- - - - 1, 0, 0, -, -, -)$  for HSQldb of version '2cr8'. It

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Table XXI. The testing models used in the case study

software	Model	MFS& masking sequence
HSQldb 2cr8	$2^9 \times 3^2 \times 4^1$	$(5_1; 6_0; 7_0) \rightarrow (5_1; 8_2; 9_2) = (5_1; 8_2; 9_1) \rightarrow (5_1; 8_3; 9_2) = (5_1; 8_3; 9_1)$
HSQldb 2.2.5	$2^0 \times 3^3$	$(6_1; 7_0) \rightarrow (5_2)$
HSQldb 2.2.9	$2^0 \times 3^3$	$(6_0) \rightarrow (0_1; 5_1; 7_0) = (0_0; 5_1; 7_0) \rightarrow (5_1; 7_0)$
JFlex 1.4.1	$2^{10} \times 3^2 \times 4^1$	$(0_0) \rightarrow (1_0)$
JFlex 1.4.2	$2^{11} \times 3^2 \times 4^1$	$(1_0; 2_1) \rightarrow (0_1)$
synthex 1	$2^0 \times 3^3 \times 4^1$	$(2_1; 3_0) \rightarrow (1_1; 2_1) = (1_0; 3_0)$
synthex 2	$2^0 \times 3^2 \times 4^1$	$(4_1; 6_0; 7_1; 8_0) \rightarrow (1_1; 3_1; 5_1) \rightarrow (2_0; 3_1; 6_0)$
synthex 3	$2^0 \times 3^3$	$(2_1; 3_0) \rightarrow (1_0) = (4_1) \rightarrow (6_0; 7_0)$
synthex 4	$2^1 \times 3^2 \times 4^1$	$(0_1; 2_1; 5_0; 6_1) \rightarrow (2_1; 4_0) = (6_1; 7_0) \rightarrow (3_0; 4_0; 5_0)$
synthex 5	$2^4 \times 3^3 \times 4^2$	$(0_0; 1_1; 3_0; 6_1; 8_0) \rightarrow (2_0; 3_0; 4_1)$
synthex 6	$2^9 \times 3^2$	$(2_0; 7_1; 8_1) \rightarrow (3_1; 5_1) = (4_0) \rightarrow (3_1; 6_0; 7_1) \rightarrow (3_1; 7_1; 8_0)$
synthex 7	$2^{10} \times 3^1 \times 4^1$	$(3_1; 4_0; 5_0) \rightarrow (2_0; 4_0; 7_1; 9_0) \rightarrow (6_1; 10_0; 11_1)$
synthex 8	$2^{11} \times 3^1 \times 4^1$	$(1_0; 3_1; 4_0; 7_1; 9_0; 12_1) \rightarrow (0_0; 2_1; 3_1; 7_1; 10_0; 11_1)$
synthex 9	$2^4 \times 4^3$	$(3_1; 5_0) \rightarrow (5_0; 6_1)$
synthex 10	$2^1 \times 3^3 \times 4^1$	$(0_1; 3_0; 4_1; 7_0) \rightarrow (2_0; 3_0; 5_1) = (2_0; 3_0; 5_0)$

is noted that we using ' $\rightarrow$ ' and ' $=$ ' to describe the masking sequence of each MFS, in which ' $\rightarrow$ ' means the left MFS in this operator can mask the right MFS of this operator, e.g.,

$(5_1; 6_0; 7_0) \rightarrow (5_1; 8_2; 9_2)$  means if  $(5_1; 6_0; 7_0)$  appears in the test case, then  $(5_1; 8_2; 9_2)$  will not be triggered. Operator ' $=$ ' means that these two MFS will not mask each other.

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6.2.1. *Study setup.* After preparing the subjects under testing, we then apply our approach (augment the FIC BS with replacing strategy) to identify the MFS of each SUT listed in Table XXI. Specifically, for each SUT we select each test case that failed during testing and feed these into our FCI approach as the input. Then, after the identifying process is over, we record the MFS each got (referred to as *identified MFS* for convenience) and the extra test cases it needed. For the traditional FIC BS approach, we designed the same experiment as that used for our approach, but as the object being tested under test had multiple faults for which the traditional FIC BS cannot be applied directly, we adopted two traditional strategies on the FIC BS algorithm, i.e., regard as one fault and distinguish faults described in Section 3.2. The purpose of recording the generated additional test cases is to later quantify the additive cost of our approach.

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We next compared the identified MFS of each approach with the prior MFS to quantify the degree that each suffers from masking effects, such that we can figure out how much better our approaches perform better than traditional ones when the SUT contains potential masking effects. There are five metrics we need to calculate in this study, which are listed as follows:

- (1) The number of the common combinations that appeared in both identified MFS and prior MFS. We denote this metric as *accurate number* later.
- (2) The number of the identified combinations which are the parent combinations of some prior failure-inducing combinations. We refer this metric as *the parent number*.
- (3) The number of the identified combinations that are the sub combinations of some prior failure-inducing combinations, which are referred to as *the sub number*.
- (4) The number of ignored failure-inducing combinations. This metric counts these combinations in prior failure-inducing combinations, which are irrelevant to the identified combinations. We label this metric as *ignored number*.



- (5) The number of irrelevant combinations. This metric counts these combinations in these identified combinations ~~that, which~~ are irrelevant to the prior failure-inducing combinations. It is referred to ~~as~~ the irrelevant number.

Among these five metrics, ~~the~~ high accurate number value indicates FCI approaches ~~that~~ performs effectively, while ~~the~~ ignored number and irrelevant number indicate the degree of deviation for the FCI approaches. ~~The~~ For parent number and sub number, ~~they~~ indicate ~~the~~ FCI approaches that ~~although with additional noisy information~~, can determine part parameter values ~~for about~~ the failure-inducing combinations, ~~although with additional noisy information~~.

Besides these specific metrics, we ~~also in addition~~ give ~~an~~ composite criteria to measure the overall performance of each approach. The computing formula for ~~the~~ composite criteria is as follows:

$$\frac{\text{accurate} + \text{related}(\text{parent}) + \text{related}(\text{sub})}{\text{accurate} + \text{parent} + \text{sub} + \text{irrelevant} + \text{ignored}}$$

In this formula, *accurate*, *parent*, *sub*, *irrelevant*, ~~and ignored~~ ~~respectively~~ represents the value of each specific metric. *related* function gives the similarity between the schemas (either parent or sub) and the real MFS. The similarity between two schemas  $S_A$  and  $S_B$  is computed as:

$$\text{Similarity}(S_A; S_B) = \frac{\text{the same elements in } S_A \text{ and } S_B}{\max(\text{Degree}(S_A); \text{Degree}(S_B))}$$

For example, the similarity of (- 1 2 - 3) and (- 2 2 - 3) is  $\frac{2}{3}$ , as the same elements of this two schemas ~~are~~ the third and last elements, and both of ~~these~~ two schemas ~~are~~ ~~third-degree~~ ~~is 3-degree~~.

So the *related* function is the summation of similarity of all the parent or sub schemas with their corresponding MFS.

6.2.2. *Results and discussion*. Table XXII depicts the results of the second case study. There are eight main columns in this table, (~~too wide so~~ we break it into two part-s), which ~~respectively~~ indicates: the ~~object to which~~ subject we apply ~~the~~ FCI approach, the number of accurate MFS each approach identified, the number of identified schemas which ~~are~~ the sub-schema parent-schema of some prior MFS, ~~the~~ the number of ignored prior MFS, the number of identified schemas which ~~are~~ irrelevant to all the prior MFS, the metric which gives the overall evaluation of each approach, and the extra test cases each algorithm needed. For each main column, there are four sub-columns which ~~respectively depict~~ the results for the FCI with *regard as one fault* strategy, FCI with *distinguish faults* strategy, FCI with replacing strategy based on ILP test case searching, and FCI with replacing strategy based on randomly searching. The last one ~~is will be~~ discussed in the next case study.

We first observed that, the results of two traditional strategies—*regard as one fault* and *distinguish faults*—~~are~~ coincide with the formal analysis in section 4. ~~Specifically, in specific~~, the former has more sub-schemas of MFS than the latter for all the 15 subjects, and the latter has more parent-schemas of MFS than ~~the~~ the former. For the 'ignored MFS' metric, as we have executed all the failing test cases, we get 0 ignored MFS for all the approaches. So ~~in order~~ to evaluate this metric ~~offor~~ the approaches, we record ~~it this metric~~ for each FCI ~~one~~ test case one ~~at a~~ time and take the average value as the result, which is listed in ~~the~~ parentheses. We also found in most cases (except synthez 5 and synthez 6) ~~that~~ the approach with *distinguish* strategy get more ignored MFS than ~~the others another one~~, which ~~is~~ also coincides with the formal analysis. And for the 'irrelevant MFS', we found *regard as one fault* strategy in most cases ~~geot~~ more 'irrelevant MFS' than ~~the others another~~, which ~~was~~ also as expected.

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Table XXII. Result of the evaluation of each approach

Subject	accurate				sub				parent				ignore			
	One	Distin	ILP	Rand	One	Distin	ILP	Rand	One	Distin	ILP	Rand	One	Distin	ILP	Rand
HSQL2cr8	2	3	5	5	3	2	0	2	0	2	4	5	0(2.04)	0(3.91)	0(4.0)	0(4.1)
HSQL2.2.5	2	2	2	2	1	0	0	0	0	1	1	1	0(0.83)	0(1.0)	0(1.0)	0(1.0)
HSQL2.2.9	2	3	2	2	3	1	1	1	0	4	1	1	0(1.33)	0(2.83)	0(2.56)	0(2.56)
JFlex1.4.1	2	2	2	2	0	0	0	0	0	1	0	0	0(0.75)	0(1.0)	0(1.0)	0(1.0)
JFlex 1.4.2	2	2	2	2	1	0	0	0	0	1	1	1	0(0.67)	0(1.0)	0(1.0)	0(1.0)
synthez 1	2	1	1	1	2	0	0	0	0	2	2	2	0(1.0)	0(2.0)	0(2.0)	0(2.0)
synthez 2	3	3	3	3	10	0	0	0	0	10	6	6	0(1.96)	0(2.0)	0(2.0)	0(2.0)
synthez 3	4	3	3	3	4	2	2	2	0	5	5	5	0(2.08)	0(2.84)	0(2.84)	0(2.84)
synthez 4	3	3	3	3	10	3	2	3	0	6	5	5	0(2.6)	0(2.8)	0(2.9)	0(2.85)
synthez 5	2	2	2	2	4	0	0	0	0	2	1	1	0(1.02)	0(1.0)	0(1.0)	0(1.0)
synthez 6	2	3	3	3	15	4	4	4	0	8	8	8	0(1.99)	0(3.72)	0(3.72)	0(3.72)
synthez 7	3	3	3	3	10	0	0	0	0	6	6	6	0(2.04)	0(2.0)	0(2.0)	0(2.0)
synthez 8	2	2	2	2	4	0	0	9	0	4	3	3	0(1.05)	0(1.0)	0(1.0)	0(1.0)
synthez 9	2	1	1	1	1	0	0	0	0	1	1	1	0(0.8)	0(1.0)	0(1.0)	0(1.0)
synthez 10	0	1	1	1	3	1	1	1	0	0	0	0	0(1.0)	0(1.46)	0(1.31)	0(1.31)

irrelevant				overall				test cases			
One	Distin	ILP	Rand	One	Distin	ILP	Rand	One	Distin	ILP	Rand
0	2	0	34	0.57	0.65	0.88	0.23	8.125	11.92	17	17.72
7	0	0	0	0.25	0.83	0.83	0.83	8.67	7.67	10.17	11.3
4	0	0	0	0.4	0.74	0.8	0.8	9.167	8.61	11.72	13.14
25	0	0	0	0.07	0.83	1	1	23.5	6.5	8	9.68
25	0	0	0	0.09	0.83	0.83	0.83	20.5	9	11.67	13.12
15	17	17	17	0.19	0.11	0.11	0.11	16.5	18	41.75	41.75
1	0	0	0	0.54	0.76	0.8	0.8	11.19	14.12	16.96	17.08
13	9	9	9	0.28	0.34	0.34	0.34	12.73	9.46	14.18	14.44
9	9	9	9	0.35	0.4	0.39	0.39	9.91	13.02	18.55	18.45
1	0	0	0	0.65	0.88	0.92	0.92	13.04	13.7	14.77	14.84
8	10	10	10	0.38	0.36	0.36	0.36	14.91	11.75	15.37	15.71
5	0	0	0	0.39	0.83	0.83	0.83	12.77	14.59	16.44	16.53
3	0	0	0	0.56	0.9	0.91	0.91	24.45	25.25	26.27	26.37
0	0	0	0	0.75	0.83	0.83	0.83	6.8	8	9	9
0	2	1	1	0.5	0.47	0.58	0.58	9.08	11	15.38	15.53

We then observed that our approach can perform better than the two traditional strategies. The advantages are shown by the more accurate MFS and less irrelevant schemas. Our approach also identified the least number of sub-schemas. As for the 'parent-schema' metric, our approach performs better than 'distinguish faults' but not as well as 'regard as one fault'. This is because our strategy is actually based on the 'distinguish faults' strategy (the main difference is that our strategy filters these unsatisfied test cases). However, our approach is not as good as perform at the 'ignored MFS' metric. The possible reason for this may be that the unsatisfied test cases we discard may contain some useful information about the MFS. Above all, our approach achieves the best performance compared with the other another two strategies, which can be shown in the 'overall' metric. The overall metric indicates that our approach performs better than 'distinguish faults' strategy, and which is better than the 'regard as one fault' strategy.

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We further observed that, the extra cost ~~of generateding~~ test cases for our approach is acceptable. ~~In fact, when compared to theing with~~ 'distinguish strategy', our approach ~~needed an average of justin av-erage need just~~ 3 or ~4 more test cases, and when compared ~~toing with the~~ 'regard as one fault', our approach ~~needed lesscan even need smaller~~ test cases in some ~~instances cases~~ (JFlex 1.4.1, JFlex 1.4.2, synthez 3 and synthez 6). This is because the extra test cases the FCI needed lies ~~inon~~ what the MFS is, the difference at the identified MFS for FCI approaches will make their needed test cases differs greatly, so that the cost for replacing test cases in our approach may ~~just~~ have little influence on the ~~number of~~ final ~~needed~~ test cases ~~needed~~.

Therefore, the answer we got for Q2 is ~~that~~. Our approach ~~achievesget a~~ better performance than ~~the~~ two traditional strategies when handling masking effects ~~at anin a~~ acceptable extra cost.

### 6.3. Evaluating the ILP-based test case searching method

The third empirical study aims to evaluate the efficiency of the ILP-based test case searching component in our approach. To conduct this study, we implemented ~~an~~ FCI approach which is also augmented ~~by thewith~~ replacing test cases strategy, but the test case replacing process is by random.

6.3.1. *Study setup.* The setup of this case study ~~is~~ based on the second case study, ~~and usesin fact, we use~~ the same SUT model ~~as~~ in Table XXI. Then, we apply the newly randomly searching based FCI approach ~~to identifyon identifying~~ the MFS in these prepared SUTs. ~~In order to~~ To avoid the bias that comes ~~from~~ the randomness, we repeat the newly approach 30 times to identify the MFS in each faileding test case. We will compute the average additional test cases as well as other metrics listed in the precise section of the random-based approach.

6.3.2. *Result and discussion.* The evaluation of this random-based approach is also ~~shownlist ed~~ in Table XXII. Compared ~~ing with to~~ our ILP-based approach, we observed that there is little distinction between them ~~in terms ofat~~ the metrics: accurate schemas, parent-schemas, sub-schemas, ignored schemas, irrelevant schemas (the ILP-based approach performs ~~a~~ slightly better, ~~e.g.~~, for subject HSQL2cr8, ~~the~~ ILP-based approach identified less sub-parents, parent and irrelevant schemas than ~~the~~ random-based ~~procedure~~). This is because ~~theis~~ two approaches ~~is~~ both ~~use the~~ test case replacing strategy, so when examining ~~ing~~ a schema, both ~~of this~~ two ap-proaches may ~~obtainget~~ the same result, although the test cases generated will be different. However, when considering the cost ~~of~~ each approach ~~will take~~, we ~~can~~ find the ILP-based approach performs better, which can reduce ~~s inin the~~ average ~~to~~ 1 or ~2 test cases ~~less~~ than random-based ~~procedureone~~.

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In summary, the answer for Q3 is ~~that~~. ~~How~~ to searching ~~for~~ a satisfied test case ~~does have in-fluence on~~ the performance ~~offer~~ our approach, especially ~~regardingat~~ the number of ~~needed~~ extra test cases ~~needed~~, and the ILP-based test cases can handle the masking effects at a relatively smaller cost than then ~~the~~ random-based approach ~~can~~.

### 6.4. Comparisoncompare with Feedback-driven combinatorial testing

The FDA-CIT [Yilmaz *et al.* 2013] approach can handles masking effects so that the covering array it generates can cover all the t-way schemas without being masked by the MFS. There is an integrated FCI approach in ~~of the~~ FDA-CIT, of which this FCI approach has two versions, ~~i.e.~~, ternary-class and multiple-class. In this paper, we use the multiple-class version ~~foras~~ our comparatived approach, as Yilmaz ~~it is claimed~~ that the multiple-class version performs better than the former ~~in~~ [Yilmaz *et al.* 2013].

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6.4.1. *Study setup.* As the FCI approach of FDA-CIT ~~uses~~ a post-analysis (classified tree) technique on given test cases, in this paper ~~the same as~~ [Yilmaz *et al.* 2013] we fed the FDA-CIT the covering array as the input ~~just as was done in the Yilmaz study~~ [Yilmaz *et al.* 2013].

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The covering arrays we generated ~~are~~ ranged from 2-4 ways. The covering array generating method we used is that contained in [Cohen *et al.* 2003].

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as it can be easily extended with constraints dealing and seeds injecting [Cohen *et al.* 2007b], which is needed in the FDA-CIT process. As different test cases will influence the results of the characterization process, ~~so we repeated~~ generating 30 different 2-4 way covering arrays and fed them ~~into the~~ FDA-CIT. Then, we recorded the results of this approach, which consists of the metrics mentioned in the second case study.

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Besides the FDA-CIT, we also applied our ILP-based approach ~~to the on~~ generated the covering array. ~~Specifically in specific~~, for each failing test case in the covering array, we separately applied our approach to identify the MFS in that case. In fact, we can reduce the number of ~~much~~ extra test cases if we utilize the other test cases in the covering array [Li *et al.* 2012]), but we didn't utilize the information ~~to for~~ simplify the experiment. We then merged all the test cases that our approach needed for each failing test case in the covering array, and we also merged other metrics listed in the second case study for each failing test cases.

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As our approach generated different test cases from the FDA-CIT, we also ~~let used~~ the multiple-class FCI approach of FDA-CIT to characterize the MFS using the test cases generated by our approach, so that we ~~could can get~~ obtain a ~~fairer more fair~~ result with which to ~~evaluate when evaluating~~ the FCI approach.

**6.4.2. Result and discussion.** We list the average result of the 30-times experiment for the FDA-CIT, ILP-based approach, and FDA-CIT using our test cases (FDAs), respectively, in Table XXIII. The result is organised ~~almost the same way as in~~ Table XXII, except that we have added a ~~t~~ column which indicates the strength of the covering array we generated for this experiment.

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Table XXIII: Comparison with FDA-CIT

Subject	t	accurate			sub			parent			ignore		
		FDA	ILP	FDA-s	FDA	ILP	FDA-s	FDA	ILP	FDA-s	FDA	ILP	FDA-s
HSQL2cr8	2	0.17	2.27	1.57	0.57	0	0	0.17	0.4	2.17	3.87	2.3	2
	3	1.47	3.67	1	0	0	0	4.67	2	6.07	0.63	0.3	0.17
	4	0.83	4.8	1	0	0	0	9.03	3.37	8	0	0	0
HSQL2.2.5	2	1	1.97	0.37	0	0	0	2.4	0.73	3.8	0.4	0	0
	3	0	2	0.4	0	0	0	5	1	3.8	0	0	0
	4	0	2	0.33	0	0	0	5	1	4	0	0	0
HSQL2.2.9	2	0.9	1.77	0.9	0	0.77	9	1.47	0.47	6.8	1.93	0.53	0
	3	1	2	0.83	0	1	0	5.13	0.93	7.1	0.2	0	0
	4	1	2	1	0	1	0	5.87	1	6.7	0	0	0
JFlex 1.4.1	2	0	2	0	0	0	0	4.03	0	4	0	0	0
	3	0	2	0	0	0	0	4	0	0	0	0	4
	4	0	2	0	0	0	0	4	0	0	0	0	0
JFlex 1.4.2	2	0.3	1.97	0.93	0	0	0	3.6	1	2.16	0.03	0	0
	3	0	2	0.97	0	0	0	5	1	2.1	0	0	0
	4	0	2	1	0	0	0	5	1	2	0	0	0
synthez 1	2	0.97	1	1	0	0	0	1.7	1.93	2	0	0.07	0
	3	1	1	1	0	0	0	2	2	2	0	0	0
	4	1	1	1	0	0	0	2	2	2	0	0	0
synthez 2	2	0.17	1.3	0.73	0.37	0	0	0	0.4	2.37	2.27	1.2	1.03
	3	0.73	2.23	0.5	0	0	0	1.9	1.3	7.1	1.2	0.43	0.53
	4	0.63	2.97	0.1	0	0	0	5.3	2.33	16.1	0.53	0	0
synthez 3	2	0.43	2.97	0.73	0	0.93	0	4.3	1.73	5.3	0.47	0.17	0.5

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	3	0.2	3	0.87	0	1.57	0	7.2	3.67	6.57	0.07	0	0
	4	0.03	3	1	0	1.97	0	10.4	3	6	0	0	0
synthéz 4	2	0.3	2.3	0.33	0.07	0.63	0	2.63	1.97	7.7	1.93	0.63	0.4
	3	0.37	2.97	0.07	0	1.26	0	6.5	3.53	10.97	0.83	0.07	0
	4	0.07	3	0	0	1.77	0	11.7	4.67	11.4	0	0	0
synthéz 5	2	0.2	1.2	0.8	0.3	0	0	0.1	0.03	0.83	1.4	0.77	0.97
	3	0.87	1.4	0.53	0	0	0	0.5	0.23	3.03	1	0.6	0.77
	4	0.7	1.9	0.37	0	0	0	1.77	0.33	6.5	0.9	0.1	0.03
synthéz 6	2	0.23	2.63	0.17	0.2	2	0	2.93	1.63	9.63	2.6	0.5	0.4
	3	0.1	3	0.1	0	2.83	0	7.4	3.83	12.5	1.2	0.17	0.03
	4	0	3	0	0	3.8	0	10.2	6.03	14.5	0.47	0	0
synthéz 7	2	0.13	1.43	0.83	0.23	0	0	0.1	0.63	1.4	2.53	1.03	0.93
	3	0.87	2.17	0.93	0	0	0	0.43	1.23	2.97	1.77	0.17	0.13
	4	1	2.87	1	0	0	0	3.23	2.53	4.6	0.27	0	0
synthéz 8	2	0	0.2	0.17	0.03	0	0	0	0	0.03	0.3	0.13	0.13
	3	0	0.6	0.5	0.1	0	0	0	0	0.03	0.97	0.47	0.53
	4	0	1.33	0.8	0.1	0	0	0	0.07	0.67	1.53	0.4	0.5
synthéz 9	2	1	1	1	0	0	0	0.46	0.6	0.77	0.53	0	0.23
	3	1	1	1	0	0	0	1	1	1	0	0	0
	4	1	1	1	0	0	0	1	1	1	0	0	0
synthéz10	2	0	0.63	0	0.6	1	0.2	0	0	0.83	1.8	0.37	1.9
	3	0.07	0.97	0	0.23	1	0.03	0.36	0	1.9	2.23	0.03	1.97
	4	0	1	0	0.07	1	0	1.7	0	2	1.87	0	2

t	irrelevant			overall			test cases		
	FDA	ILP	FDA-s	FDA	ILP	FDA-s	FDA	ILP	FDA-s
2	2.53	0	1.97	0.12	0.51	0.39	23.6	70.1	70.1
3	3	0	1.47	0.51	0.87	0.6	76.6	241.8	241.8
4	0.97	0	0	0.65	0.9	0.71	183.5	606.6	606.6
2	1.4	0	0.1	0.38	0.87	0.56	26.7	68.8	68.8
3	0	0	0	0.52	0.83	0.56	67	202.4	202.4
4	0	0	0	0.53	0.83	0.56	130.1	503.3	503.3
2	2.37	0	0.2	0.28	0.72	0.58	29.2	78.3	78.3
3	0.1	0	0	0.61	0.8	0.61	72.8	221.7	221.7
4	0	0	0	0.64	0.8	0.62	129.8	560.3	560.3
2	0	0	0	0.49	1	0.5	30.5	87.3	87.3
3	0	0	0	0.5	1	0.5	73.4	269.2	269.2
4	0	0	0	0.5	1	0.5	190.6	724.7	724.7
2	0.63	0	0	0.5	0.83	0.62	34.3	106.9	106.9
3	0.03	0	0	0.52	0.83	0.61	72.3	305.7	305.7
4	0	0	0	0.53	0.83	0.61	186.8	836.9	836.9
2	0.33	14.3	0	0.66	0.13	0.78	40.3	342.87	342.87
3	0	16.73	0	0.78	0.12	0.78	93.4	809.1	809.1
4	0	17	0	0.78	0.12	0.78	218.8	1532.8	1532.8
2	1.37	0	1.2	0.11	0.52	0.4	19.77	54.4	54.4
3	2.2	0	1.33	0.36	0.82	0.52	59.5	171.5	171.5
4	2.6	0	1	0.44	0.89	0.54	152.7	415.1	415.1

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2	1.03	3.77	1.13	0.37	0.46	0.37	48.6	138.7	138.7
3	0.83	6.77	0.07	0.38	0.38	0.44	106.3	315.3	315.3
4	0.43	8.56	0	0.38	0.34	0.45	147.9	565.7	565.7
2	3.4	1.4	1.97	0.24	0.6	0.44	42.7	142.2	142.2
3	2.5	3.43	1.03	0.39	0.54	0.51	86.5	373.2	373.2
4	1.33	6.73	0.03	0.48	0.44	0.55	202.2	899.7	899.7
2	0.7	0	1	0.2	0.59	0.4	21.9	46.9	46.9
3	0.37	0	1.63	0.46	0.71	0.43	76.9	150.3	150.3
4	1.87	0	2.03	0.34	0.92	0.54	232.9	433.2	433.2
2	3.03	3.7	2	0.19	0.42	0.37	45.7	132.6	132.6
3	2.3	6.5	0.67	0.31	0.38	0.43	99.5	338.9	338.9
4	1.8	9.1	0.03	0.37	0.36	0.44	152.6	781.9	781.9
2	1.93	0	1.97	0.09	0.61	0.38	20.3	58.8	58.8
3	3.2	0	2.87	0.2	0.88	0.44	52.6	164.7	164.7
4	4.5	0	2.27	0.35	0.9	0.51	145.3	413.1	413.1
2	0.17	0	0.3	0.01	0.1	0.05	16.1	45.2	45.2
3	0.63	0	0.87	0.02	0.3	0.17	43.1	64.3	64.3
4	1.4	0	0.93	0.04	0.67	0.41	109.3	145.6	145.6
2	0.63	0.6	0.67	0.54	0.7	0.6	36.2	43.4	43.4
3	0	0	0	0.83	0.83	0.83	84.3	145	145
4	0	0	0	0.83	0.83	0.83	188	291.6	291.6
2	1.5	0.3	3.97	0.23	0.61	0.17	23.4	84.9	84.9
3	4.03	0.53	3.97	0.13	0.66	0.2	73.4	263.2	263.2
4	4.03	1	4	0.21	0.58	0.2	202.2	685.9	685.9

From this result, we can first observe that in all the cases our ILP-based approach can identify more accurately identify the MFS and ignores less ignored-MFS than the FDA-CIT approach. For the metric 'parent-schema', 'sub-schema', and 'irrelevant schemas', there are ups and downs on both sides. With respect to the 'overall metric', we can find our approach has a significant advantage over the FDA-CIT, but it also requires needed much many more test cases than FDA-CIT.

We note it is noted that, when applying the multiple-class FCI to the test cases generated using our approach, their 'overall' metric is still not as good as our ILP-based approach, but may show some improvement over the original FDA-CIT.

Another interesting observation is that overall performance in most cases is increasing with the t, which it can be easily understood. More test cases will contain more information about the MFS, so that we can utilize them to identify the MFS more precisely.

So the answer for the Q4 is: that Our approach can achieve a more precise result for about the MFS, and the FDA-CIT can perform the identifying process using a small amount of extra test cases. Both of these two approaches have their ups and downs, choosing which approach in practice will depend on the specific scenario you test.

#### 6.5. Threats to validity

There are several threats to the validity of these empirical studies. First, we have only surveyed two types of open-source software with five different versions, of which the program scale is medium-sized. This may impact the generality of our observations. Although we believe it is quite possible a common phenomenon in most software that

contains multiple faults which can mask each other, we need to investigate more software to support our [beliefconjecture](#).

ACM Transactions on Embedded Computing Systems, Vol. 9, No. 4, Article 39, Publication date: March 2010.

The second threat comes from the input model we built. As we focused on the option-s related to the perfect combinations and only augmented it with some noise options, there is a chance we will get different results if we choose other noise options. More options need to be tested/different options needed to be opted to see whether our result is common or just appears in some particular input models.

The third threat is that we just evaluated one FCI approach – FIC BS [Zhang and Zhang 2011], so further works need to examine more algorithms in this field to obtain a more general result.

## 7. RELATED WORKS

Shi and Nie presented a further testing strategy for fault revealing and failure diagnosis [Shi et al. 2005], which first tests the SUT with a covering array, then reduces the value schemas contained in the failed test case by eliminating those appearing in the passed test cases. If the failure-causing schema is found in the reduced schema set, failure diagnosis is completed with the identification of the specific input values which caused the failure; otherwise, a further test suite based on SOFOT is developed for each failed test case, testing is repeated, and the schema set is then further reduced, until no more failures are found or the fault has been located. Based on this work, Wang proposed an AIFL approach which extended the SOFOT process by mutating the changing strength in each iteration that of characterizing failure-inducing combinations [Wang et al. 2010].

Nie et al. introduced the notion of Minimal Failure-causing Schema (MFS) and proposed the OFOT approach which is an extension of extended from SOFOT that can isolate the MFS in SUT [Nie and Leung 2011]. The approach mutates one value with different values for that parameter, hence generating a group of additional test cases each time to be executed. Compared with SOFOT, this approach strengthens the validation of the factor under analysis and also can detect the newly imported faulty combinations.

Delta debugging proposed by Zeller [Zeller and Hildebrandt 2002] proposed by Zeller is an adaptive divide-and-conquer approach to locate interaction faults. It is very efficient and has been applied in a real software environment. Zhang et al. also proposed a similar approach that can efficiently identify the failure-inducing combinations that have no overlapped part efficiently [Zhang and Zhang 2011]. Later, Li improved the delta-debugging based failure-inducing combination by exploiting the useful information in the executed covering array [Li et al. 2012].

Colbourn and McClary proposed a non-adaptive method [Colbourn and McClary 2008]. Their approach extends the covering array to the locating array to detect and locate interaction faults. C. Martinez proposed two adaptive algorithms. The first one requires an adequate safe value as the assumption, and the second one removes the assumption when the number of values of each parameter is equal to 2 [Martinez et al. 2008; 2009]. Their algorithms focus on identifying the faulty tuples that have no more than 2 parameters.

Ghandehari et al. defined the suspiciousness of tuple and suspiciousness of the environment of a tuple [Ghandehari et al. 2012]. Based on this, they rank the possible tuples and generate the test configurations. They further utilized the test cases generated from the inducing combination to locate the faults inside the source code [Ghandehari et al. 2013].

Yilmaz proposed a machine learning method to identify inducing combinations from a combinatorial testing set [Yilmaz et al. 2006]. They constructed a classified tree to analyze the covering arrays and detect potential faulty combinations. Besides this, Fouche' [Fouche' et al. 2009] and Shakya [Shakya et al. 2012] made some improvements in identifying failure-inducing combinations based on Yilmaz's work.

Our previous work [Niu et al. 2013] have proposed an approach that utilizes the tuple relationship tree to isolate the failure-inducing combinations in a failing test case. One

novelty of this approach is that it can identify the overlapped faulty combinations. This work also alleviates the problem of introducing newly failure-inducing combinations in additional test cases.

In addition to the studies that aims at identifying the failure-inducing combinations in test cases, there are others that some studies focus on working around the masking effects.

With having known masking effects in prior, Cohen [Cohen *et al.* 2007a; 2007b; 2008] studied the impacts of that the masking effects that render some generated test cases invalid in CT, and they He proposed an the approach that integrates the incremental SAT solver with a covering array that generating algorithms to avoid these masking effects in the process of generating test cases, generating process. Further study was conducted [Petke *et al.* 2013] to show the fact that with considering constraints, the higher-strength covering arrays with early fault detection are is practical. Besides, additional constraints impacting in CT were studied in the following works: works like [Garvin *et al.* 2011; Bryce and Colbourn 2006; Calvagna and Gargantini 2008; Grindal *et al.* 2006; Yilmaz 2013].

Chen *et al.* addressed the issues of shielding parameters in combinatorial testing and proposed the Mixed Covering Array with Shielding Parameters (MCAS) to solve the problem caused by shielding parameters [Chen *et al.* 2010]. The shielding parameters can disable some parameter values to expose additional interaction errors, which can be regarded as a special case of masking effects.

Dumlu and Yilmaz proposed a feedback-driven approach to work around the masking effects [Dumlu *et al.* 2011]. Specifically, they in specific, it first used CTA to classify the possible failure-inducing combinations and then eliminate them and generate new test cases to detect possible masked interaction in the next iteration. They further extended their work [Yilmaz *et al.* 2013], by proposing in which they proposed a multiple-class CTA approach to distinguish faults in SUT. In addition, they empirically studied the impacts on both ternary-class and multiple-class CTA approaches.

Our work differs from these ones mainly in the fact that we formally studied the masking effects on FCI approaches and further proposed a divide-and-conquer strategy to alleviate this impact.

## 8. CONCLUSIONS

Masking effects of multiple faults in SUT can bias the results of traditional failure-inducing combinations identifying approaches. In this paper, we formally analysed the impact of masking effects on FCI approaches and showed that the both two traditional strategies are both inefficient in handling such impact. We further presented a divide-and-conquer strategy for FCI approaches to alleviate such this impact.

In our the empirical studies, we extended FCI approach—FIC BS [Zhang and Zhang 2011] with our strategy. The comparison between our approach and with its traditional approaches was was performed conducted on several kinds of open-source software. The results indicated that our strategy do assists the traditional FCI approach in achieving getting a better performance when facing masking effects in SUT. In our approach, We also empirically evaluated the the efficiency of the test case searching component in our approach by comparing it with the randomly searching based FCI approach, of which the results shows that the ILP-based test case searching method can perform much more efficiently. At last, we compared our approach with existing techniqs for handling masking effects handling technique—FDA-CIT [Yilmaz *et al.* 2013], and observed that our approach acheved can get a more precise result which can

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support better debugging aids, though our approach ~~need~~<sup>generates</sup> more test cases than FDA-CIT.

As ~~for~~<sup>for</sup> future work, we need to do more empirical studies to make our conclusions more general. Our current experiments ~~focus on~~<sup>focus on</sup> ~~several~~ middle-sized software. ~~We~~<sup>We</sup> would like to extend our approach ~~into~~<sup>into</sup> more complicated, ~~and~~ large-scaled testing scenarios. Another promising work in the future is to combine ~~the~~<sup>the</sup> white-box testing technique to ~~facilitate obtaining more accurate results from FCI approaches when handling masking effects.~~<sup>facilitate obtaining more accurate results from FCI approaches when handling masking effects.</sup>

~~effects.~~ We believe that figuring out the fault levels of different bugs through ~~the~~ white-box testing technique is helpful to reduce misjudgements in the failure-inducing combinations identifying process. ~~And~~ last, ~~because~~as the extent to which ~~at the~~ FCI suffers from masking effects varies ~~within~~ different algorithms, ~~a~~the combination of different FCI approaches ~~would be desirable~~is desired in the future to further improve ~~the performance for~~identifying MFS for mul-tiple faults.

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