Fault localization in constraint programs

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—Constraint programs such as those written in high-level modeling languages (e.g., OPL [15], ZINC [14], or COMET [16]) must be thoroughly verified before being used in applications. Detecting and localizing faults is therefore of great importance to lower the cost of the development of these constraint programs. In a previous work, we introduced a testing framework called CPTEST enabling automated test case generation for detecting non-conformities [13]. In this paper, we enhance this framework to introduce automatic fault localization in constraint programs. Our approach is based on constraint relaxation to identify the constraint that is responsible of a given fault. CPTEST is henceforth able to automatically localize faults in optimized OPL programs. We provide empirical evidence of the effectiveness of this approach on classical benchmark problems, namely Golomb rulers, n-queens, social golfer and car sequencing.

I. Introduction

These last years have seen the explosion of high-level constraint modeling languages, including OPL [15], COMET [16], ZINC [14], or Essence [7]. In parallel, several propositions were made to use constraint programs in critical applications. For example, constraint programs were developed for e-commerce [9], air-traffic control and management [6], [11] or critical software development [4], [8]. As any other programs, constraint programs written in high-level modeling languages must be thoroughly verified before being used on real-size instances of satisfaction or optimization problems. In [13], we introduced a testing framework where a first highly declarative constraint model is took as a reference to detect non-conformities within a refined and optimized constraint program solving the same problem. These non-conformities result from faults introduced during the refinement process, coming either from the absence or the bad formulation of constraints. Our testing framework was shown useful to detect non-conformities but it reveals itself poor at identifying the constraint responsible of the fault. In fact, the user resorts to explore manually one by one each of the constraints of its constraint model, which can be cumbersome even for small programs. For example, consider the N-queens problem solved by the OPL program of Fig.1. When $N = 30$, using a simple declarative model of N-queens, the testing framework of [13] reports a non-conformity: $[30\ 29\ 28\ ...1]$. Although this vector indeed solves all the constraints of Fig.1, it shows a fault in the OPL program which obviously places many queens on the same diagonal. Therefore, at least one constraint of the model

```
      using CP;

      int n=...;
      range Domain=1..n;

      dvar int queens[Domain] in Domain;
      dvar int diag1[Domain];
      dvar int diag2[Domain];

      subject to{

      forall( i in Domain)
a.    diag1[i]==queens[i]+i;

      forall( i in Domain)
b.    diag2[i]==queens[i]-i;

c.    sum(i in Domain) queens[i]==(n*(n+1) div 2);

      forall(ordered i,j in Domain)
d.    diag1[i]<=diag1[j];

      forall(ordered i,j in Domain)
e.    diag2[i]!=diag2[j];

      forall(ordered i,j in Domain)
f.    queens[i]!=queens[j];
      }
```

Fig. 1: N-queens problem in OPL.

is incorrectly formulated. In this paper, we address the problem of automatically locating the constraint that is responsible of such a non-conformity. Automatic fault localization is a difficult problem, even for conventional programs. The most successful approach in the Software Engineering community is the Jones, Statsko and Harrold's algorithm [10] that compares execution traces in order to guess the source code statements that are more likely to contain a fault. Their implementation called Tarantula takes both successful and unsuccessful execution traces of a sequential program as inputs, and by crossing these traces, it ranks the statements from the most suspicious to the less suspicious. The idea of the ranking algorithm is that faulty statements more frequently appear on unsuccessful traces. A related approach proposed by Cleve and Zeller aims at tracing back the causes of fault introduction [3], which is the ultimate goal of fault localization. Recently, it has been shown that the Jones, Statsko and Harrold's algorithm can be rephrased by using classical data mining indicators [1] leading to possible generalization to multi-faults localization. These approaches are well suited for sequential programs as the control flow is data-driven, i.e., any execution trace depends

on the values of input variables. However, they are not suited for constraint programs as the control flow is constraint-driven in this case, i.e., the order on which constraints are considered by the language interpreter is usually not determined by input values. In other words, comparing traces on distinct instances does not help to localize faults. A trend in constraint program debugging has been to analyze a single trace via generic trace models [5], [12]. In the context of the OADymPPaC[1] project, several post-mortem trace analyzers such as Codeine for Prolog and Morphine [12] for Mercury, ILOG Gentra4CP, and JPalm/JChoco have been developed. All these tools can help the developer to understand and optimize his constraint program, but they are not dedicated to automatic fault localization. Following the Shapiro's algorithmic debugging approach, the user still has to query the trace and user interaction during the debugging process is mandatory.

In this paper, we introduce a fault localization approach that is fully automated for OPL programs. This approach is based on systematic constraint relaxation by making use of the ILOG CP constraint solver. The idea is to solve auxiliary constraint programs built over the OPL constraint program under test and the reference model used to specify the problem. We provide an algorithm that takes the faulty constraint program and a non-conformity as inputs and returns either a single constraint or a set of constraints that are responsible of the fault. For example, in the OPL program of Fig.1, our algorithm reports constraint `d` as responsible of the given non-conformity. Looking at constraint `d` permits to spot that operator `=<` should be replaced by `!=`. We present our implementation called CPTEST enabling automatic fault localization. We provide empirical evidence on classical benchmark problems, namely golomb rulers, n-queens, social golfer and car sequencing that our approach is not only applicable but also efficient to localize faults in OPL programs.

The rest of the paper is organized as follows: Section II gives an overview of the constraint programs testing framework of [13] and introduces some notations. Section III presents our automatic fault localization algorithm. Section IV presents CPTEST and the empirical results we got on n-queens, golomb rulers, social golfers and car sequencing. Section V concludes this paper and draws some perspectives to this work.

II. Background

CP aims at solving satisfaction or optimization problems. When one faces a problem specification, one usually writes down a first declarative constraint model that faithfully represents the problem. We have high confidence in this model but playing with it rapidly shows that it cannot solve large instances of the problem. Then, this model is refined using classical techniques such as constraint reformulation, redundant and surrogate constraint addition, global constraint replacement, or static symmetry-breaking constraints. This refinement leads to have an optimized constraint model tuned to address difficult instances. We think that most of the faults are introduced in this refinement step. In our previous work [13], we introduced a testing framework taking the first declarative model as an oracle for detecting non-conformities in the optimized model. We defined various formal conformity relations handling the cases where a single solution is found, all the solutions are found or a cost function has to be optimized.

[1]http://contraintes.inria.fr/OADymPPaC/

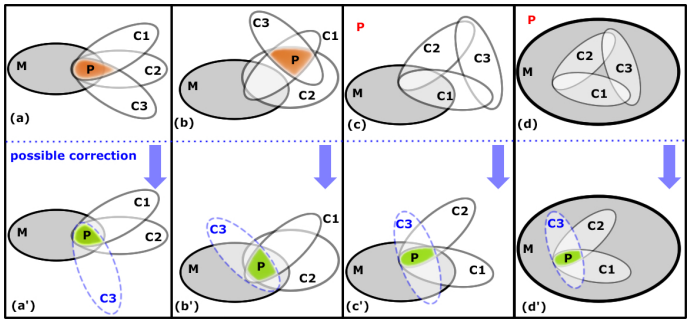

Fig. 2: Fault localization cases.

A. Notations

In this section, we briefly give the necessary notations to understand the rest of the paper. M denotes the initial declarative model called the *Model-Oracle* and P denotes the *Constraint Program Under Test (CPUT)*. $Sol(M)$ (resp. $sol(P)$) denotes the set of solutions of the model-oracle (resp. CPUT) where M possesses at least one solution($sol(M) \neq \emptyset$). Considering unsatisfiable model-oracles could be interesting for some applications but we excluded these cases in order to avoid considering equivalence of unsatisfiable models. The difference of two sets E and F is noted $E \backslash F \triangleq \{x/(x \in E) \wedge (x \notin F)\}$. The general conformity relation between the model-oracle M and the CPUT P is given by the following definition:

Definition 1 ($conf$):

$$P \ conf \ M \ \Leftrightarrow sol(P) \neq \emptyset \ \wedge \ sol(P) \subseteq sol(M)$$

B. Non-conformity detection

As proving conformity on any instance of a problem is undecidable in the general case, we have proposed in [13], test algorithms aiming at detecting non-conformities. For a given instance, a non-conformity is either a solution of the CPUT P that is not a solution of the model-oracle M, or P is reduced to fail (i.e., $sol(P) = \emptyset$). Systematic non-conformities detection can be performed by combining the negation of a constraint of the model-oracle with the constraints of P (i.e., $P \wedge \neg C_i$ where $C_i \in M$). Badly formulating a constraint in P can remove and/or add solutions.

III. Fault localization

Once a non-conformity is detected, one faces the problem of localizing the faulty constraint. The major requirement on which our approach is based is the *single fault hypothesis*,

i.e., there is only one constraint that is faulty in P. This requirement might appear as being restrictive but it has been shown that complex faults usually result from the coupling of single faults (a.k.a. the coupling effect [10]). In other words, faults that come from the interaction of several constraints are less likely to appear than single faulty constraint. Therefore, in our approach, when a non-conformity is found, we suppose that the CPUT P misses a single constraint or has only one faulty constraint in it.

A. Intuitions

Fig.2 depicts four distinct cases where the CPUT P does not conform the model oracle M (P $\neg conf$ M), i.e., there is a solution of P and not of M (**part (a, b)**) or $sol(P) = \emptyset$ (**part (c, d)**), where P is a conjunction of three constraints $C_1 \wedge C_2 \wedge C_3$. In Fig.2, P is represented by the intersection of the three constraints and possible corrections are shown in blue.

- **Part(a)** exhibits a set of non-conformities (i.e., solutions of P but not of M) where P shares solutions with M (i.e., $sol(M) \cap sol(P) \neq \emptyset$). P is faulty as it contains C_3 a badly formulated constraint such that $sol(P) \backslash sol(M) \neq \emptyset$. In fact, after having localized C_3, this model could be corrected as shown in **part(a')**.
- **Part(b)** exhibits another set of non-conformities where $sol(P) \backslash sol(M) \neq \emptyset$ and $sol(M) \cap sol(P) = \emptyset$. In this example, we have

$$\begin{cases} sol(M) \cap sol(C_1) \cap sol(C_2) \neq \emptyset \\ sol(M) \cap sol(C_1) \cap sol(C_3) = \emptyset \\ sol(M) \cap sol(C_2) \cap sol(C_3) = \emptyset \end{cases}$$

  hence, the faulty constraint can be localized as being C_3. **Part(b')** shows a possible correction of P by revising C_3.
- **Part(c)** exhibits a case where P is unsatisfiable. Here again, we have

$$\begin{cases} sol(M) \cap sol(C_1) \cap sol(C_2) \neq \emptyset \\ sol(M) \cap sol(C_1) \cap sol(C_3) = \emptyset \\ sol(M) \cap sol(C_2) \cap sol(C_3) = \emptyset \end{cases}$$

  hence C_3 is localized as the faulty constraint and should be revised as proposed in **part(c')**.
- Finally, **Part(d)** shows a case where P is unsatisfiable but differs from the previous one as

$$\begin{cases} sol(M) \cap sol(C_1) \cap sol(C_2) \neq \emptyset \Rightarrow C_3 \text{ may be faulty} \\ sol(M) \cap sol(C_1) \cap sol(C_3) \neq \emptyset \Rightarrow C_2 \text{ may be faulty} \\ sol(M) \cap sol(C_2) \cap sol(C_3) \neq \emptyset \Rightarrow C_1 \text{ may be faulty} \end{cases}$$

  In this case, the faulty constraint cannot be localized and the set $\{C_1, C_2, C_3\}$ is returned as an over-approximation. In **part(d')**, we chose C_3 as a possible correction.

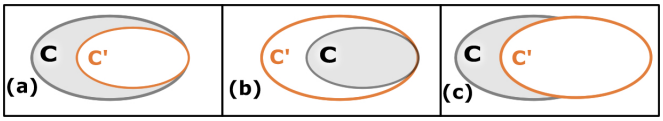

Fig. 3: Faulty constraint.

There are three distinct cases when considering non-conformities within P w.r.t. M: if C' is a faulty version of a given constraint C, then C' can either removes actual solutions (such as in part(a) in Fig.3), either add "new solutions" (part(b) in Fig.3) or both (part(c) in Fig.3).

B. The fault localization process

Our fault localization process is based on the following definitions and property. Formally speaking, given a CPUT P formed of $\{C_1, C_2, ...C_n\}$ constraints that are not conform w.r.t. its Model-Oracle M, then we introduce the notion of *suspicious constraint* as follows:

Definition 2 (Suspicious constraint):
C_i is suspicious in P w.r.t. M
$\equiv M \wedge \{C_1, C_2..., C_{i-1}, C_{i+1}...C_n\}$ is satisfiable.
P does not conform M iff either P is unsatisfiable or there exists a non-conformity test case nc such as $nc \in sol(P) \backslash sol(M)$. Our fault localization process aims at reporting the set of suspicious constraints:

Definition 3 (SuspiciousSet): $SuspiciousSet(P) \equiv \{C \in P : C$ is suspicious in P w.r.t. $M\}$
In the example of Fig.2, the fault localization process will return $Suspicious(P) = \{C_1, C_2, C_3\}$ for part(a) and part(d) as no one of these three constraints may be faulty while it will return singleton $\{C_3\}$ for both part(b) and part(c), showing that the faulty constraint is actually C_3. Note that, by construction, the set $Suspicious(P)$ is the smallest set containing all the suspicious constraints and then the over-approximation provided by this approach is also the more precise.

C. Algorithm

Based on the previous definitions, we propose an algorithm called *locate* that automatically localize suspicious constraints in P. Algo.1 takes as inputs the Model-Oracle M, the CPUT P and a non-conformity nc that has been automatically detected by other means [13]. The special case where P is unsatisfiable and then there is no nc is handled by a special tag. This algorithm returns $SuspiciousSet(P)$ noted $rev(\{C_1, .., C_m\})$ that may be a singleton in the most favorable case or all the constraints of P in the worst case. The algorithm returns also a second set $addSet$ for the special case where all the constraints of P are suspicious, and a non-conformity point nc exists. In this case, nc satisfies P, but does not satisfy some single constraint in M, according to the testing process [13]. The *checking* algorithm computes $addSet$, the subset of M constraints that does not satisfy nc: some of these constraints could be caught in P in order to eliminate this non-conformity point.

Algorithm 1 locate(M, P, nc)

```
1: set ← ∅
2: addSet ← ∅
3: for each C_i ∈ P do
4:    if sol(M ∧ P\{C_i}) ≠ ∅ then
5:       set ← set ∪ {C_i}
6:    end if
7: end for
8: if (set = P) ∧ (nc ≠ ∅) then
9:    addSet ← checking(M, nc)
10: end if
11: return (rev(set), addSet)
12:
13:
14: checking(B, nc):
15: if B = ∅ then
16:    return ∅
17: else
18:    for each C_i ∈ B do
19:       if nc ⊨ C_i then
20:          return checking(M\{C_i}, nc)
21:       else
22:          return {C_i}∪ checking(M\{C_i}, nc)
23:       end if
24:    end for
25: end if
```

D. Correctness and completeness

Providing that the underlying constraint solver is correct and complete, Algo.1 is correct as it will necessary return the faulty constraint within $SuspiciousSet(P)$. As $sol(M \wedge P \backslash \{C_i\}) \neq \emptyset$ is a sufficient condition for assessing that C_i is actually a faulty constraint and Algo.1 loops on all the constraints, no suspicious constraint can be missed. But, this condition is not necessary as, by hypothesis, only a single constraint is faulty. Thus, algo.1 is not complete and can return an over-approximation under the form of a set of suspicious constraints. Roughly speaking, algo.1 can return false alarms even in the case where a correct version of P is submitted for fault localization. Note also that Algo.1 can return all the constraints of P making the fault localization totally useless. Hopefully, this case is not frequent as it requires the conjunction of many unlikely events such as shown in Fig.4. In this example, there are three constraints where each pair of constraints shares common solutions.

IV. Experiments

All our experiments were performed on Intel Core2 Duo CPU 2.40Ghz machine with 2.00 GB of RAM and all the models we used to perform these experiments are available online at (www.irisa.fr/celtique/lazaar/CPTEST).

A. CPTEST

In this section, we give a brief overview of CPTEST, a first testing framework for constraint programs written on OPL. CPTEST includes a complete OPL parser and a backend process that produces dedicated OPL programs as output that have to be solved to detect and localize faults. The tool implements a process to detect fault and Algo.1 to localize this fault. CPTEST is based on ILOG CP optimizer 2.1.

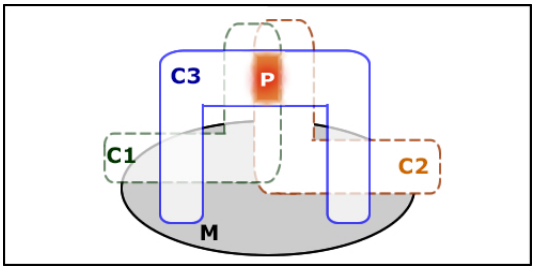

Fig. 4: Pathologic case

The objective of our current experiment was to check that CPTEST can automatically detect and localize fault, using standard a fault injection process [2]. Then, we fed CPTEST with faulty CPUTs of four well-known CP problems, namely n-queens, social golfer, golomb rulers and car sequencing problems and we tried to localize faults by working on several instances from the easiest to the hardest.

B. n-queens problem

The problem of placing n queens on an $n \times n$ chessboard is a classical problem where the model-oracle can be given by three constraints (noted `m_ct1`,`m_ct2` and `m_ct3`), the first one insures that all queens are placed differently on their column, the second and the third constraint insure that no two queens are placed on the same upper or lower-diagonal on the chessboard. We improved this model by adding new data structures, redundant, surrogate and global constraints. We have produced 7 different faulty CPUTs (P1 to P7)[2] for n-queens using fault injection.

Tab.I shows the results given by CPTEST on each faulty n-queens CPUT ($n = 8$). It shows the number of constraints and where fault was injected (e.g. `p5_ct3` for P5), P6 and P7 are messing a part of n-queens specification where the fault injected respectively in `p6_ct3` and `p7_ct1` leads the CPUTs to accept new solutions. (part(b) Fig.3).

Tab.I shows also the non-conformity detected after the testing phase, the results of localization phase and its time consumption. P1, P2, P3 and P4 have no solution ($sol(Pi) = \emptyset$) where the fault injected reduces them to fail. For instance let us take P3, the fault injected in is as follows:

```
p3_ct11: sum(i in Domain) queens[i]==(n*(n+1)/2);
```

turned to

```
p3_ct11: sum(i in Domain) queens[i]==(n+(n+1)/2);
```

[2]We recall that all models and CPUTs are available on (www.irisa.fr/celtique/lazaar/CPTEST).

TABLE I: Fault detection and localization of n-queens problem

	8-queens	# consts.	fault injected	non-conformity detected
Test	**P1**	12	p1_ct11	$sol(P1) = \emptyset$
	P2	12	p2_ct12	$sol(P2) = \emptyset$
	P3	12	p3_ct11	$sol(P3) = \emptyset$
	P4	12	p4_ct12	$sol(P4) = \emptyset$
	P5	5	p5_ct3	q1
	P6	3	p6_ct3	q2
	P7	2	p7_ct1	q3
non-conformity		q1= [1 5 1 1 4 8 8 4]		
q2= [7 8 3 2 4 1 5 6], q3= [8 4 3 6 5 7 2 1]				
Localization	**8-queens**	**fault localized**		**time**
	P1	(rev(p1_ct11),∅)		2.09s
	P2	(rev(p2_ct12),∅)		1.64s
	P3	(rev(p3_ct11),∅)		1.57s
	P4	(rev(p4_ct12),∅)		1.59s
	P5	(rev(p5_ct3),∅)		0.62s
	P6	(rev(P6), (m_ct2,m_ct3))		4.12s
	P7	(rev(P7), (m_ct2,m_ct3))		3.01s

CPTEST returns (rev(p3_ct11),∅) , here the set of suspicious constraint is the singleton p3_ct11 the faulty constraint that has to be revised. The faults are localized for the four first programs in few seconds by pointing each time the faulty constraint that has to be revised.

The fault injected in P5 leads it to have bad n-queens solutions, testing phase highlights this non-conformity ([1 5 1 1 4 8 8 4]). For localization phase, CPTEST points the faulty constraint in less than a second and returns p5_ct3 to be revised.

For P6 and P7 the fault is that, respectively, p6_ct3 and p7_ct1 do not catch a part of n-queens specification. The two CPUTs accept consequently new solutions. CPTEST detects non-conformities that are bad solutions revealing faults in P6 and P7. For localization, let us take P6, CPTEST returns (rev(P6),(m_ct2,m_ct3)) , in less than five seconds. The set of suspicious constraint is here equals to P6, CPTEST returns also a set of M constraints (m_ct2, m_ct3) that should be considered in P6.

C. Social golfer problem

Social golfer is one of the famous problems in the CSPLib (prob010). We have m social golfers, n weeks and k groups of l size. Each golfer plays once a week in groups of l golfers. The problem is to build a schedule of play for all golfers over the n weeks such that no golfer plays in the same group as any other golfer more than one time.

The model-oracle can be built by two constraints (m_ct1 and m_ct2), the first one to specify that each group has exactly l golfers (group size). The second one to say that each pair of golfers meets only at most once.

The model-oracle can after be improved using static symmetry breaking. The symmetry can be broken by selective assignment. We get a model with five constraints, we inject in each constraint a fault to get at the end five faulty CPUTs (P1 to P5). We launch CPTEST on these faulty CPUTs to first detect fault and after localize them. We take an instance of the problem with 9 golfers (3 groups of 3 golfers) playing during 4 weeks.

TABLE II: Fault detection and localization of social golfer problem

	social golfer	# constrs.	fault injected	non-conformity detected
Test	**P1**	5	p1_ct1	$sol(P1) = \emptyset$
	P2	5	p2_ct2	nc1
	P3	5	p3_ct3	$sol(P3) = \emptyset$
	P4	5	p4_ct4	$sol(P4) = \emptyset$
	P5	5	p5_ct5	$sol(P5) = \emptyset$
non-conformity		nc1= [[1 1 1 1][1 2 2 2][1 3 3 3]		
[2 1 3 3][2 2 2 1][2 2 1 1][3 3 3 2][3 1 1 2][3 3 2 3]]				
Localization	**social golfer**	**fault localized**		**time**
	P1	(rev(p1_ct1),∅)		1.04s
	P2	(rev(P2), (m_ct2))		0.18s
	P3	(rev(p3_ct3),∅)		1.05s
	P4	(rev(p4_ct4,p4_ct5),∅)		1.03s
	P5	(rev(p5_ct5),∅)		1.15s

Tab.II shows the results given by CPTEST on each faulty CPUT. The fault injected in P1, P3 and P5 are respectively on p1_ct1 , p3_ct3 and p5_ct5 . These faults reduce the solution space to empty for the three CPUTs, so there are non-conform to the model-oracle. For instance, let us take P5, the fault in p5_ct5 is:

```
p5_ct5: forall (g in 1..golfers, w in 1..weeks:
                  w >= 2 && g <= groupSize )
            assign[g,w] == g;
```

turned to

```
p5_ct5: forall (g in 1..golfers, w in 1..weeks:
                  w >= 2 && g <= groupSize )
            assign[g,g] == w;
```

CPTEST localizes the fault (in $\simeq 1s$) and returns the singleton p5_ct5 the constraint to be revised.

The fault injected in p2_ct2 leads P2 to accept new solutions. In this case, P2 can return bad solutions. CPTEST detects one of them by testing, $nc1$ is a non-conformity (a bad solution of social golfer) where golfer 3 and golfer 4 play in the same group ($group3$) over 2 weeks ($3rd$ and $4th\ week$). CPTEST returns (rev(P2),(m_ct2)) that the developer has to reformulate a constraint in P2 to catch (m_ct2) the second constraint of the model-oracle.

P4 is a case where CPTEST returns a set of suspicious constraint. The fault is injected in p4_ct4 and CPTEST returns (p4_ct4, p4_ct5) an over-approximation of constraints. The two constraints in P4 break symmetries. Let us imagine that the search space SR can be divided in two symmetric sets: $SR \equiv S_1 \cup S_2$ where p4_ct5 removes S_2. p4_ct4 divides S_1 in two symmetric sets ($S_1 \equiv S_3 \cup S_4$) and removes S_4. By adding the two constraints, the search space is reduced to S_3. The fault injected to p4_ct4 removes S_1 where p4_ct5

TABLE III: Fault detection and localization of Golomb rulers problem

	Golomb rulers	# consts	fault injected	non-conformity detected
Test	**P1**	2	p1_ct2	[0 1 3 6]
	P2	4	p2_ct3	[0 1 6 11]
	P3	5	p3_ct3	[0 5 6 11]
	P4	9	p4_ct5	$sol(P4) = \emptyset$
	P5	9	p5_ct1	$sol(P5) = \emptyset$
	P6	9	p6_ct2	[0 1 6 11]
	P7	9	p7_ct9	$sol(P7) = \emptyset$
	Golomb rulers	**fault localized**		**time**
Localization	**P1**	(rev(P1), (m_ct2))		0.32s
	P2	(rev(P2), (m_ct2))		0.82s
	P3	(rev(P3), (m_ct2))		1.15s
	P4	(rev(p4_ct5),∅)		1.87s
	P5	(rev(p5_ct1),∅)		1.62s
	P6	(rev(P6), (m_ct2))		2.14s
	P7	(rev(p7_ct6,p7_ct9),∅)		1.92s

TABLE IV: Fault detection and localization of car sequencing problem

	car sequencing	# constraints	fault injected	non-conformity detected
Test	**P1**	2	p1_ct2	slots1
	P2	3	p2_ct3	slots2
	P3	3	p3_ct2	slots3
	P4	3	p4_ct2	$sol(P4) = \emptyset$
	P5	6	p5_ct1	$sol(P5) = \emptyset$
	P6	6	p6_ct6	$sol(P6) = \emptyset$
	P7	6	p7_ct5	$sol(P7) = \emptyset$
	slots1= [4 5 3 6 4 6 5 1 3 2] slots2= [4 6 3 1 5 2 3 5 4 6] slots3= [5 2 3 6 1 4 3 6 4 5]			
	cSeq	**fault localized**		**time**
Localization	**P1**	(rev(P1), (m_ct2))		0.46s
	P2	(rev(P2), (m_ct2))		0.23s
	P3	(rev(P3), (m_ct2))		0.67s
	P4	(rev(p4_ct2),∅)		0.87s
	P5	(rev(p5_ct1),∅)		1.29s
	P6	(rev(p6_ct6),∅)		1.34s
	P7	(rev(p7_ct5, p7_ct6),∅)		1.28s

removes S_2, in this case the search space is reduced to empty and either p4_ct4 or p4_ct5 can be revised.

D. Golomb rulers

A Golomb ruler is a set of m marks ($0 = x_1 < x_2 ... < x_m$) where the $m(m-1)/2$ distances $\{x_j - x_i | 1 \leq i < j \leq m\}$ are distinct. A ruler is of order m and its length is x_m. The objective is to find an optimal ruler (minimal length) of order m.
A first declarative model (model-oracle) includes two constraints. m_ct1 to order the marks and m_ct2 to have different distances between these marks.

We improve this model using different techniques, the use of new data structure (e.g. d for distances), the addition of a global constraint (allDifferent(d)), the addition of surrogate and redundant constraints. We also break symmetry by adding specific constraints. We obtain at the end 7 faulty CPUT by fault injection.

We take a small instance of Golomb rulers ($m = 4$). We launch CPTEST on these faulty CPUTs where Tab.III shows the results. The three first CPUTs accept new solutions where the fault injected is of type part(b) Fig.3. For each of these three CPUTs a non-conformity is reached. For example, if we take P2, CPTEST returns after testing [0 1 6 11] that is a bad Golomb ruler where 6-1=11-6. CPTEST returns after localization (rev(P2),(m_ct2)), here P2 has to catch the second constraint of the model-oracle by reformulating one of its constraints.
P4 and P5 are also non-conform to the model-oracle where $sol(Pi) = \emptyset$. The faults are respectively in p4_ct5 and p5_ct1. Let us take P4 to show the injected fault:

```
p4_ct5: allDifferent(all(ind in indexes ) d[ind]);
```

turned to

```
p4_ct5: forall(i in m..2*m)
            count(all(j in indexes) d[j],i)==1;
```

CPTEST returns a singleton as suspecious constraints set for P4 and P5 (resp. p4_ct5 and p5_ct1) in a reasonable time consumption.

P6 have a bad formulation on p6_ct2 and CPTEST returns a non-conformity. For localization, CPTEST returns m_ct2 to be caught in P6.

On P7, we injected one fault at p7_ct9 ($\neq$ turned to $=$). This fault reduces $sol(P7)$ to empty. CPTEST returns two suspicious constraints (p7_ct6 and p7_ct9). This is due to the interference created by the injected fault between the faulty p7_ct9 and p7_ct6 where the two constraints are dedicated to a static symmetry breaking.

E. Car sequencing

Car sequencing is an interesting CP problem that tries to find an assembly line of cars for a car-production company where cars are grouped on classes. Each class represents cars with some specific options. The assembly line must satisfy some option capacity constraints.

The model-oracle of car sequencing is taken from the OPL book [15]. The model-oracle is composed of two constraints (m_ct1 and m_ct2). The first one expresses demand constraints for how many cars of a given class have to be produced. The second one expresses capacity constraints of the form l outof u for: Each sub-sequence of u cars, a unit can produce at most l cars with a given option.

We improve the original model and we follow the same approach as for the precedent problems by injecting faults. We have at the end 7 faulty CPUTs.

We took an instance of the problem with an assembly line of 10 cars, 6 classes and 5 options. Tab.IV shows the results of CPTEST for fault detection and localization on car sequencing problem.
The three first CPUTs (P1, P2 and P3) have the same characteristics that accept new solutions and are non-conform

to the model-oracle, the faults are injected respectively in `p1_ct2`, `p2_ct3` and `p3_ct2`. CPTEST returns a non-conformity point for the three first CPUTs (resp. `slots1`, `slots2` and `slots3`) that are bad assembly lines. To localize faults, CPTEST returns all constraints as an over-approximation. It proposes a model-oracle constraint `m_ct2` to be caught in the CPUTs.

P4, P5 and P6 have a faulty constraint (resp. `p4_ct2`, `p5_ct1` and `p6_ct6`). The faults injected in these CPUTs reduce the set of solutions to empty and CPTEST detects this non-conformity.
If we take P5, the fault injected is a bad formulation as:

```
p5_ct1: forall(i in Cars) sum(j in Slots)
          ((slot[j]==i)*(one[j]))==demandV[i];
```

turned to

```
p5_ct1: pack(slot, slot, one);
```

This constraint is returned by CPTEST (`(rev(ct1),`$\emptyset$) in $1.29s$.

In P7, the fault is injected in `p7_ct5` where P7 is non-conform to the model-oracle. CPTEST returns in localization a set of suspicious constraints (`p7_ct5`, `p7_ct6`).

V. Conclusion

In this paper, we introduced a novel approach for automatic fault localization in constraint programs. According to our knowledge, this is the first time an approach that is not based on post-mortem trace analysis is proposed: the advantage being that our approach does not require any user interaction. We enhanced CPTEST, our CP testing framework for OPL programs, with automatic fault localization. And we got empirical evidence that shows our approach is efficient to localize fault in OPL programs. The experimental evaluation was performed on classical benchmarks such as Golomb rulers, n-queens, social golfers and car sequencing. In many cases, CPTEST can localize exactly the constraint responsible of a reported non-conformity efficiently. In a few cases, several constraints are proposed among which the faulty constraint is necessarily included. However, our approach is currently built on the hypothesis that a single constraint is responsible of the non-conformity which is a limitation. Further work includes the removal of this limitation as well as the extension of CPTEST to automatic correction of faulty constraints.

References

[1] Peggy Cellier, Mireille Ducassé, Sébastien Ferré, and Olivier Ridoux. Dellis: A data mining process for fault localization. In *Proc. of the 21st International Conference on Software Engineering & Knowledge Engineering (SEKE'2009)*, pages 432–437, 2009.

[2] Jeffrey A. Clark and Dhiraj K. Pradhan. Fault injection. *Computer*, 28(6):47–56, 1995.

[3] Holger Cleve and Andreas Zeller. Locating causes of program failures. In *ICSE '05: Proceedings of the 27th international conference on Software engineering*, pages 342–351, New York, NY, USA, May 2005.

[4] H. Collavizza, M. Rueher, and P. Van Hentenryck. Cpbpv: A constraint-programming framework for bounded program verification. In *Proc. of CP2008*, LNCS 5202, pages 327–341, 2008.

[5] P. Deransart, M. V. Hermenegildo, and J. Maluszynski, editors. *Analysis and Visualization Tools for Constraint Programming, Constrain Debugging (DiSCiPl project)*, volume 1870 of *Lecture Notes in Computer Science*. Springer, 2000.

[6] P. Flener, J. Pearson, M. Agren, Garcia-Avello C., M. Celiktin, and S. Dissing. Air-traffic complexity resolution in multi-sector planning. *Journal of Air Transport Management*, 13(6):323 – 328, 2007.

[7] A.M. Frisch, M. Grum, C. Jefferson, B. Martnez, and H.I. Miguel. The design of essence: a constraint language for specifying combinatorial problems. In *Proceedings of IJCAI'07*, pages 80–87, 2007.

[8] A. Gotlieb. Tcas software verification using constraint programming. *The Knowledge Engineering Review*, 2009. Accepted for publication.

[9] Alan Holland and Barry O'Sullivan. Robust solutions for combinatorial auctions. In *ACM Conference on Electronic Commerce (EC-2005)*, pages 183–192, 2005.

[10] J. A. Jones, M. J. Harrold, and J. Stasko. Visualization of test information to assist fault localization. In *ICSE '02: Proceedings of the 24th International Conference on Software Engineering*, pages 467–477, 2002.

[11] U. Junker and D. Vidal. Air traffic flow management with ilog cp optimizer. In *International Workshop on Constraint Programming for Air Traffic Control and Management*, 2008. 7th EuroControl Innovative Research Workshop and Exhibition (INO'08).

[12] L. Langevine, P. Deransart, M. Ducassé, and E. Jahier. Prototyping clp(fd) tracers: a trace model and an experimental validation environment. In *WLPE*, 2001.

[13] N. Lazaar, A. Gotlieb, and Y. Lebbah. On testing constraint programs. In *Proc. of Principles of Constraint Programming, CP'2010*, Sept. 2010.

[14] K. Marriott, N. Nethercote, R. Rafeh, P. J. Stuckey, M. Garcia De La Banda, and M. Wallace. The design of the zinc modelling language. *Constraints*, 13(3):229–267, 2008.

[15] P. Van Hentenryck. *The OPL optimization programming language*. MIT Press, Cambridge, MA, USA, 1999.

[16] Pascal Van Hentenryck and Laurent Michel. *Constraint-Based Local Search*. The MIT Press, 2005.