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Generating Range Fixes for Software Configuration

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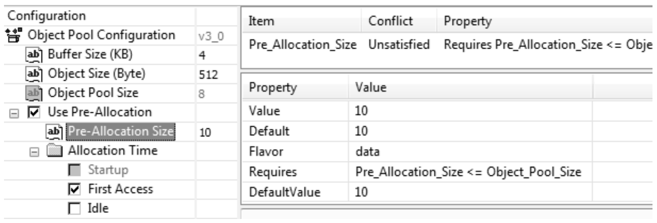


Configuration	
Object Pool Configuration	v3_0
Buffer Size (KB)	4
Object Size (Byte)	512
Object Pool Size	8
✓ Use Pre-Allocation	
Pre-Allocation Size	10
Allocation Time	
▨ Startup	
✓ First Access	
☐ Idle	

Item	Conflict	Property
Pre_Allocation_Size	Unsatisfied	Requires Pre_Allocation_Size <= Obje

Property	Value
Value	10
Default	10
Flavor	data
Requires	Pre_Allocation_Size <= Object_Pool_Size
DefaultValue	10

Figure 1: The eCos Configurator

Abstract—**To prevent configuration errors, highly configurable software often allows defining constraints over the available options. As these constraints can be complex, fixing a configuration that violates one or more constraints can be challenging. Although several fix-generation approaches exist, their applicability is limited because (1) they typically generate only one fix, failing to cover the solution that the user wants; and (2) they do not fully support non-Boolean constraints, which contain arithmetic, inequality, and string operators.**

This paper proposes a novel concept, *range fix*, for software configuration. A range fix specifies the options to change and the range of values at these options. We also design an algorithm that automatically generates range fixes for a violated constraint, based on Reiter's theory of diagnosis. We have evaluated our approach on data from five open source projects, showing that, for our data set, the algorithm generates complete fix lists that are mostly short and concise, in a fraction of a second.

I. Introduction

A growing share of software exposes sophisticated configurability to handle variations in user and target-platform requirements. Large enterprise resource planning systems (e.g., SAP) need to be tailored to different business contexts. Software product lines often supply software embedded in specific hardware products like automobiles and airplanes [1]. Operating systems (e.g., Linux and eCos) need to run on different hardware platforms like desktops, servers and mobile devices. To configure Linux for instance, users typically select the CPU architecture (e.g., x86 or ARM), the type of filesystem (e.g., ext4 or JFS), and the graphics driver (e.g., ATI or NVIDIA).

These configuration options are usually described with dedicated languages that document their hierarchy and constraints over their selection. For instance, the Linux kernel uses Kconfig, and eCos—an embedded configurable operating system—uses CDL [2]. These real-world languages fall under the umbrella of variability modelling languages [3]. Another popular variability modelling language is feature models [4]. Developed jointly by researchers and practitioners, it has been successfully implemented in commercial product-line tools like pure::variants [5] and Gears [6], and has an expressiveness comparable to that of Kconfig and CDL [7].

Configurators translate these models into interactive configuration interfaces, such as the one in Figure 1, and assist users in arriving at a correct and complete configuration. To do so, configurators detects possible configuration errors and reports them. A configuration error is a decision that conflicts with some constraints. Satisfying these constraints is often non-trivial. Variability languages often carry advanced constructs that introduce hidden constraints [2], and constraint rules declared in different places of the variability model may have interactions. The interplay of these factors often leads to very complex situations.

Some configuration tools, like those based on Kconfig, implement an error avoidance mechanism that automatically deactivates an option when a certain constraint is violated. Inactive options are no longer available to the user unless the constraint is satisfied again. Other configurators, like the eCos configurator for CDL (Figure 1), add an interactive resolution mechanism on top of the avoidance mechanism. This approach allows violating some constraints, but proposes a fix for each violated constraint. A fix denotes a set of changes that would restore the consistency of the current configuration.

To better understand what challenges are faced by the users of modern configurators, we carried out two empirical studies of Linux and eCos. Two questionnaires were submitted to forums, mailing lists and experts with whom we collaborate. In total, we collected answers from 92 Linux users with up to 20 years of experience, and 9 eCos users with up to 7 years of experience. The full report of this study is avaible as a technical report [8]. We present here the two challenges that stand out most from this study and that are addressed in this paper:

- **Activating inactive features.** 18% of the Linux users report that, when they need to change an inactive option, they need at least a "few dozen minutes" in average to figure out how to activate it. 56% of the eCos users also consider the activation of an inactive option to be a problem.
- **Fix incompleteness.** Existing configurators generate only one fix for an error. However, there are often multiple solutions to resolving an error, and the user may prefer other solutions. 7 out of 9 eCos users have encountered situations where the *generated fix is not useful*. That claim is corroborated by Berger et al. [2] who report that eCos users complain about the incompleteness of fixes on the mailing list.

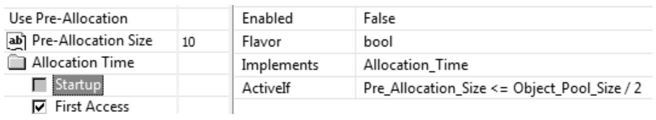
Since we also need to satisfy the corresponding constraint to activate a feature, activation is inherently the same as resolving a configuration error, and the idea of fixes would also work for activation. As a result, a possible solution for the above two problems is to generate fixes for both resolving errors and activating features, and fixes should be complete so that the user can choose the one he wants.

To achieve this goal, two main challenges need to be addressed. First, our previous study of eCos models [9] shows that non-Boolean operators, such as arithmetic, inequality, and string operators, are quite common in their constraints. In fact, the models contain four to six times more Non-Boolean constraints than Boolean ones. Non-Boolean constraints are challenging since there is often an infinite number of ways to satisfy them. Computing such infinite list of fixes is pointless. Thus, a *compact* and *intentional* representation of fixes is needed. Second, many existing approaches rely on constraint solvers to generate fixes, either using solvers for MAXSAT/MAXSMT [10] or the optimizing capability of CSP solvers [11]. However, all these solvers return only one result per call, which is not easily applicable to the generation of complete lists of fixes. A new method to generate complete lists of fixes still needs to be found.

This paper proposes a new approach to generating fixes for software configuration. Our contribution is threefold:

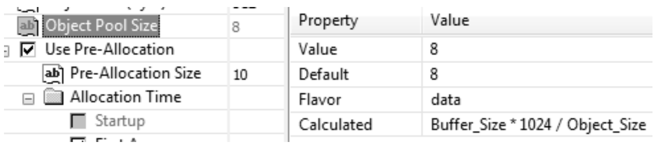
- **Range fixes.** We propose a novel concept, *range fix* (Section II), to address the first challenge. Instead of telling users what concrete changes should be made, a range fix tells them what options should be changed and in what range the value of each option can be chosen. A range fix can represent infinite number of concrete fixes and still retains the goal of assisting the user to satisfy constraints. Particularly, we discuss the desired properties of range fixes, which formalize the requirement of the fix generation problem. In addition, we also discuss how constraint interactions should be handled in our framework (Section IV).
- **Fix generation algorithm.** We designed an algorithm that generates range fixes automatically (Section III) to address the second challenge. Our algorithm builds upon Reiter's theory of diagnosis [12], [13] and SMT solvers [14]. Additionally, our algorithm is designed for a general representation of constraints and variables, which makes it potentially useful in other areas such as debugging.
- **Evaluation with eCos.** Our algorithm is (1) applied on eCos CDL (Section V) and (2) evaluated on data from five open source projects using eCos (Section VI). The evaluation compares three different fix generation strategies and concludes that the propagation strategy is the most effective one on our dataset. Specifically, for a total of 117 constraint violations, the evaluation of the propagation strategy shows that our notion of range fix leads to mostly simple (83% of the fix lists have sizes smaller than 10, where the size is measured by summing up the number of variables in all the fixes in the list) yet complete set of fixes. It also demonstrates that our algorithm can generate fixes for models containing hundreds of options and constraints in an average of 50ms and a maximum of 245ms.

Finally, we discuss threats to validity in Section VII, the related work in Section VIII and conclude the paper in Section IX.


Use Pre-Allocation
Pre-Allocation Size 10
Allocation Time
Startup
First Access

Enabled	False
Flavor	bool
Implements	Allocation_Time
ActiveIf	Pre_Allocation_Size <= Object_Pool_Size / 2

Figure 2: Option "Startup"


Object Pool Size 8
Use Pre-Allocation
Pre-Allocation Size 10
Allocation Time
Startup

Property	Value
Value	8
Default	8
Flavor	data
Calculated	Buffer_Size * 1024 / Object_Size

Figure 3: Option "Object Pool Size"

II. Range Fixes

Motivating example We now motivate our work with a concrete example based on the eCos configurator [15]. Figure 1 shows a small model for configuring an object pool. The left panel shows a set of options that can be changed by the user, organized into a tree. The lower-right panel shows the properties of the current option, defined according to the eCos models. Particularly, the *flavor* property indicates whether the option is a Boolean option or a data option. A Boolean option can be either selected or unselected; a data option can be assigned an integer or a string value. In Figure 1, "Pre-Allocation Size" is a data option; "Use Pre-Allocation" is a Boolean option.

Besides the flavor, each option may also declare constraints using *requires* property or *active-if* property. When a requires constraint is violated, an error is reported in the upper-right panel. In Figure 1, option "Pre-Allocation Size" declares a requires constraint requiring its value be smaller than or equal to "Object Pool Size", and an error is reported because the constraint is violated.

An active-if constraint implements the error avoidance mechanism. When it is violated, the option is disabled in the GUI and its value is considered as zero. Figure 2 shows the properties of the "Startup" option. This option declares that at most half of the object pool can be pre-allocated. Since this constraint is violated, the "Startup" option is disabled and the user cannot change its value.

Fixing a configuration error or activating an option requires satisfying the corresponding constraints. In order to fix the error on "Pre Allocation Size" in Figure 1, we need to look up the definition of "Object Pool Size". In Figure 3, we see that "Object Pool Size" declares a *calculated* property meaning that the value of the option cannot be modified by the user. Instead, it is determined by a declared expression. As a result, the constraint declared on "Pre-Allocation Size" is, in fact, the following:

```
Pre_Allocation_Size <=
  Buffer_Size * 1024 / Object_Size
```

Furthermore, according to the CDL semantics, a constraint is effective—and thus considered by the error checking system—only when its containing option is active, and an option is active only when its active-if constraint is satisfied and its parent option is selected. "Pre-Allocation Size" has a parent, yielding the following complete constraint:

```
Use_Pre_Allocation -> (Pre_Allocation_Size <=
   Buffer_Size * 1024 / Object_Size)
```

By analyzing the constraint, we realize that we may fix the error by one of the following changes: decreasing "Pre-Allocation Size", or increasing "Buffer Size", or decreasing "Object Size", or, more simply, disabling the pre-allocation function. Now we could choose one of these possibilities and navigate to the respective option to make the change.

This example shows that there are three sub-tasks for enabling a constraint. First, the user needs to figure out the complete semantic constraint according to the constraint language. Since variability languages often have fairly complex semantics on visibility and value control [2], it is very easy to overlook some part of the constraint. Secondly, users needs to analyze the semantic constraint and figure out how to change the options to make it satisfied. In practice, constraints can be very large. One semantic constraint we have found in a CDL model contains 55 options references and 35 constants, connected by 66 logical, arithmetic and string operators. It is very difficult to analyze such a large constraint. Thirdly, users have to navigate to the corresponding options and make the changes. Real world variability models contain thousands of options, e.g., an eCos model reported [2] contains 1244 options, which makes navigation very cumbersome [8].

Solution Our approach automatically generates a list of range fixes to help satisfy a constraint. For the error in Figure 1, we will generate the following fixes.

- `[Use_Pre_Allocation := false]`
- `[Pre_Allocation_Size: Pre_Allocation_Size <= 8]`
- `[Buffer_Size: Buffer_Size >= 5]`
- `[Object_Size: Object_Size <= 409.6]`

Each range fix consists of two parts: the option to be changed and a constraint over the options showing the range of values. The first range fix is also a concrete assignment, and will be automatically applied when selected. The other fixes are ranges. If the user selects, for example, the second fix, the configurator will highlight option "Pre-Allocation Size", prompt the range "`<=8`", and ask the user to select a value in the range.

Range fixes automate the three sub-tasks mentioned above. The semantics of CDL constructs is automatically taken into account and the constraint is automatically analyzed. The navigation is also automatically performed when applying a fix. The user only has to choose a fix and decide a value within the range of the fix.

Definitions Although different variability languages have different constructs and semantics, existing work [2], [16], [17] shows that all variability models can be converted into a set of variables (options) and a set of constraints. Our approach also builds upon this principle.

In essence, a variability language provides a universe of typed variables $\mathbf{V}$ and a constraint language $\Phi(\mathbf{V})$ for writing quantifier-free predicate logic constraints over $\mathbf{V}$. Consequently, a *constraint violation* consists of a tuple (V, e, c), where $V \subseteq \mathbf{V}$ is a set of typed variables; the current configuration e is a function assigning a type-correct value to each variable; and $c \in \Phi(V)$ is a constraint over V violated by e. A fix generation problem for a violation (V, e, c) is to find a set of range fixes to help users produce a new configuration e' such that c is satisfied, denoted as $e' \models c$.

Consider the following example of a constraint violation:

$$\begin{array}{lcl} V & : & \{m : \texttt{Bool}, a : \texttt{Int}, b : \texttt{Int}\} \\ e & : & \{m = \texttt{true}, a = 6, b = 5\} \\ c & : & (m \rightarrow a > 10) \wedge (\neg m \rightarrow b > 10) \wedge (a < b) \end{array} \tag{1}$$

All range fixes we have seen so far change only one variable, but more complex fixes are sometimes inevitable. For example, we cannot solve violation (1) by changing only one variable. Several alternative fixes are possible:

- $[m := \texttt{false},\ b : b > 10]$
- $[(a, b) : a > 10 \wedge a < b]$

The first fix contains two parts separated by ",", each changing a variable. We call each part a *fix unit*. The second fix is more complex. This fix contains only one fix unit, but the range of this fix unit is defined on two variables. When the fix is executed, the user has to choose a value for each variable within the range.

Taking the above forms into consideration, we can define a range fix. A *range fix* r for a violation (V, e, c) is a set of fix units. A fix unit can be either an *assignment unit* or a *range unit*. An assignment unit has the form of "$var := val$" where $var \in V$ is a variable and val is a value conforming to the type of var. A range unit has the form of "$U : cstrt$", where $U \subseteq V$ is a set of variables and $cstrt \in \Phi(U)$ is a satisfiable constraint over U specifying the new ranges of the variables. A technical requirement is that the variables in fix units should be disjoint, otherwise two different values may be assigned to one variable.

We use $r.V$ to denote the set of the variables to be changed in all units. We use $r.c$ to denote the conjunction of the constraints from all units. The constraint from an assignment unit "$var := val$" is $var = val$, and the constraint from a range unit "$U : cstrt$" is $cstrt$. For example, let r be the range fix $[m := \texttt{false},\ b : b > 10]$, then $r.v = \{m, b\}$ and $r.c$ is $m = \texttt{false} \wedge b > 10$.

Applying range fix r of violation (V, e, c) to e will produce a new configuration interactively. We denote all possible configurations that can be produced by applying

r to e as $r \triangleright e$, where $r \triangleright e = \{e' \mid e' \models r.c \wedge \forall_{v \in V}(e'(v) \neq e(v) \rightarrow v \in r.V)\}$

Desired Properties A simple way to generate a fix from a violated constraint is to produce a range unit where the changed variables are all variables in this constraint and the range of these variables is the constraint itself. For example, the fix for violation (1) could be $[(m, a, b) : (m \rightarrow a > 10) \wedge (\neg m \rightarrow b > 10) \wedge (a < b)]$. However, such a fix is as difficult to understand as the original constraint. In this subsection, we discuss the desired properties of range fixes.

Suppose r is a range fix for a violation (V, e, c). The first desired property is that a range fix should be correct: all configurations that can be produced from the fix must satisfy the constraint.

Property 1 (Correctness)**.** $\forall e' \in (r \triangleright e),\ e' \models c$

Each value currently assigned to a variable is a configuration decision made by the user, and a fix should alter as few decisions as possible. The second desired property is thus that a fix should change a minimal set of variables. For example, $[m := \texttt{true},\ b : b > 10]$ is preferable to $[m := \texttt{true},\ b : b > 10,\ a : a = 9]$ because the latter unnecessarily changes a, which does not contribute to the satisfaction of the constraints.

Property 2 (Minimality of variables)**.** *There exists no fix r' for (V, e, c) such that r' is correct and $r'.V \subset r.V$.*

Minimal fixes, however, might not cover all possible changes that resolve a violation, and these uncovered cases might be preferred by some users. However, as our evaluation will show, minimality is good heuristics in practice.

Thirdly, after determining a set of variables, we would like to present the maximal range of the variables. The reason is simple: extending the range over the same set of variables gives more choices, and usually neither decreases readability nor affects more existing user decisions. For example, $[m := true,\ b : b > 10]$ is better than $[m := true,\ b : b > 11]$ because it covers a wider range on b.

Property 3 (Maximality of ranges)**.** *There exists no fix r' for (V, e, c) such that r' is correct, $r'.V = r.V$ and $(r \triangleright e) \subset (r' \triangleright e)$*

Fourthly, after deciding the range over the variables, we would like to represent the range in the simplest way possible. Thus, another desired property is that a fix unit should change as few variables as possible. In other words, no fix unit can be divided into smaller equivalent fix units. We call this property *minimality of units*.

However, as we treat Φ as a general notion, our generation algorithm cannot ensure all fix units are minimal. Therefore we do not treat this property as part of the formal requirement. However, this does not seem to be a limitation in practice; all fix units generated in our evaluation contain only one variable, which are minimal by construction.

Armed with these properties of range fixes, we can define the *completeness* of a list of fixes. Since the same constraint can be represented in different ways, we need to consider the semantic equivalence of fixes. Two fixes r and r' are *semantically equivalent* if $(r \triangleright e) = (r' \triangleright e)$, otherwise they are *semantically different*.

Property 4 (Completeness of fix lists)**.** *Given a constraint violation (V, e, c), a list of fixes L is complete iff*

- *any two fixes in L are semantically different,*
- *each fix in L satisfies Property 1, 2, and 3,*
- *and any fix that satisfies Property 1, 2 and 3 is semantically equivalent to a fix in L*

Thus, a *fix generation problem* is to find a complete list of fixes for a given constraint violation (V, e, c).

III. Fix generation algorithm

In Section II we claimed that a fix should change a minimal set of variables and have a maximal range. As a result, our generation algorithm consists of three steps. (i) We find all minimal sets of variables that need to be changed. For example, in violation (1), a minimal set of variables to change is $D = \{m, b\}$. (ii) For each such set of variables, we replace any unchanged variable in c by its current value, obtaining a maximal range of the variables. In the example, we replace a by 6 and get $(m \rightarrow 6 > 10) \wedge (\neg m \rightarrow b > 10) \wedge (6 < b)$. (iii) We simplify the range to get a set of minimal, or close to minimal, fix units. In the example we will get $[m := \texttt{true},\ b : b > 10]$. Step (ii) is trivial and does not demand further developments. We now concentrate on steps (i) and (iii).

A. From constraint and configuration to variable sets

To collect all minimal variable sets, we resort to Reiter's theory of diagnosis [12]. This theory defines the problem of diagnosis and gives an incomplete algorithm for solving the problem. This algorithm was later corrected by Greiner et al. [13] and is now known as *HS-DAG* algorithm. Fundamentally, Reiter's theory assumes a constraint set that can be split into *hard* and *soft* constraints. The set of hard constraints are invariable and assumed satisfiable. The set of soft constraints can be altered and also be unsatisfiable. A *diagnosis* is a subset of soft constraints that, when removed from the set, restores the satisfiability of the whole set. The problem of diagnosis is to find all minimal diagnoses from a set of hard and soft constraints.

Given the constraint violation (V, e, c), we convert the problem of finding minimal variable sets to the problem of diagnosis by treating c as a hard constraint and converting e into soft constraints. For example, violation (1) can be converted into the following constraint set.

Hard constraint (c):
  [0] $(m \rightarrow a > 10) \wedge (\neg m \rightarrow b > 10) \wedge (a < b)$
Soft constraints (e):
  [1] $m = \texttt{true}$
  [2] $a = 6$
  [3] $b = 5$

To make the whole set satisfiable, we need to remove at least constraints $\{1, 3\}$ or constraints $\{2, 3\}$, which correspond to two variable sets $\{m, b\}$ and $\{a, b\}$.

To find all diagnoses, Reiter's theory uses an ability of most SAT/SMT solvers: finding an unsatisfiable core. An *unsatisfiable core* is a subset of the soft constraints that is still unsatisfiable. For example, the above constraint set has two unsatisfiable cores $\{1, 2\}$ and $\{3\}$.

If we cancel a constraint from each unsatisfiable core, we get a diagnosis. The HS-DAG algorithm implements this idea by building a directed acyclic graph (DAG), such that each node is labelled either by an unsatisfiable core or SAT, and each arc is labelled by a constraint that is cancelled. The union of the labels on every path from the root to a SAT node defines a diagnosis.

Figure III-A shows an HS-DAG for the above example. Suppose the constraint solver initially returns the unsatisfiable core $\{1, 2\}$, and a root node is created for this core. Then we build an arc for each constraint in the core. In this case, we build two arcs 1 and 2. The left arc is 1, so we remove constraint [1] from the set, and invoke the constraint solver again. This time the constraint solver returns $\{3\}$. We remove constraint [3] and now the constraint set is satisfiable. We create a node SAT for the edge. Similarly, we repeat the same steps for all other edges until all paths reach SAT. Finally, each path from the root to the leaf is a diagnosis. In this case, we have $\{1, 3\}$ and $\{2, 3\}$.

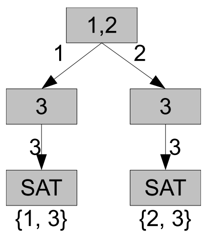


Figure 4: HS-DAG

This process alone cannot ensure that the generated diagnoses are minimal. To ensure it, three additional rules are applied to the algorithm. The details of these rules can be found in [13], and are omitted here due to space limit. Greiner et al. [13] prove that HS-DAG builds a complete set of minimal diagnosis after applying the three rules.

B. From variable sets to fixes

Equipped with the minimal variable sets, we can substitute the configuration values of the variables that do not belong to these sets into c (Step (ii)). Step (iii) is to divide this modified constraint into smaller fix units.

Since the operators in the constraints differ from one language to the other, this task is essentially domain-specific. Nevertheless, since we assume the constraint language is based on quantifier-free predicate logic, we can do some general processing. The basic idea is to convert the constraint into conjunctive normal form (CNF), and convert each clause into a fix unit. Yet, we still need to carefully make sure the fix units are disjoint and are as simple as possible.

First, if the constraints contain any operators convertible to propositional operators, we convert them into propositional operators. For example, eCos constraints contain the conditional operator ":?" such as $(m\,?\,a\,:\,b) > 10$. We convert it into propositional operators: $(\neg m \vee a > 10) \wedge (m \vee b > 10)$.

Secondly, we convert the constraint into CNF. In our example, with $\{m, b\}$, we have $(m \rightarrow 6 > 10) \wedge (\neg m \rightarrow b > 10) \wedge (6 < b)$, which gives three clauses in CNF: $\{\neg m \vee 6 > 10,\ m \vee b > 10,\ 6 < b\}$.

Thirdly, we apply the following rules repetitively until we reach a fixed point.

Rule 1 Apply constant folding to all clauses.
Rule 2 If a clause contains only one literal, delete the negation of this literal from all other clauses.
Rule 3 If a clause C_1 contains all literals in C_2, delete C_1.
Rule 4 If a clause taking the form of $v = c$ where v is a variable and c is a constant, replace all occurrences of v with c.

In our example, applying Rule 1 to the above CNF, we get $\{\neg m,\ m \vee b > 10,\ 6 < b\}$. Apply Rule 2 to the above CNF, we get $\{\neg m,\ b > 10,\ 6 < b\}$. No further rule can be applied to this CNF.

Fourthly, two clauses are merged into one if they share variables. In the example, we have $\{\neg m,\ b > 10 \wedge 6 < b\}$.

Fifthly, we apply any domain specific rules to simplify the constraints in each clause, or divide the clause into smaller, disjoint ones. These rules are designed according to the types of operators used in the constraint language. In our current implementations of CDL expressions, we use two types of rules. First, for clauses containing only linear equations or inequalities with one variable, we solve them and merge the result. Secondly, we eliminate some obviously eliminable operators, such as replacing $a+0$ with a. We also apply Rule 1 and Rule 4 shown above during the process. In the example, the second clause consists of two linear inequalities, we solve the inequalities and merge the ranges on b, we get $\{\neg m, b > 10\}$.

Finally, we convert each clause into a fix unit. If the clause has the form of v, $\neg v$, or $v = c$, we convert it into an assignment unit, otherwise we convert it into a range unit. In the example, we convert $\neg m$ into an assignment unit and $b > 10$ into a range unit and get $[m := \texttt{false},\ b :\ b > 10]$.

As mentioned before, the above algorithm does not guarantee the fix units are minimal. The reason is that we cannot ensure that the domain-specific rules in the fifth step are complete, since some common operators such those on strings are undecidable in general [18].

IV. Constraint Interaction

So far we have only considered range fixes for one constraint. However, the constraints in variability models are often interrelated; satisfying one constraint might violate another. As a result, we have to consider *multi-constraint* violation rather than single-constraint violation. A multi-constraint violation is a tuple (V, e, c, C), where V and e are unchanged, c is the currently violated constraint, and C is the set of constraints defined in the model and satisfied by e. The following example shows how a fix satisfying c can conflict with other constraints in C that were previously satisfied.

$$\begin{array}{lcl}
V & : & \{m : \texttt{Bool}, n : \texttt{Bool}, x : \texttt{Bool}, y : \texttt{Bool}, z : \texttt{Bool}\} \\
e & : & \{m \mapsto \texttt{true}, n \mapsto \texttt{false}, x \mapsto \texttt{false}, \\
 & & y \mapsto \texttt{false}, z \mapsto \texttt{false}\} \\
c & : & m \wedge n \\
C & : & \{c_2, c_3\} \text{ where} \\
 & & \quad c_2 \text{ is } n \rightarrow (x \vee y) \\
 & & \quad c_3 \text{ is } x \rightarrow z
\end{array} \tag{2}$$

If we generate a fix from (V, e, c), we obtain $r = [n := \texttt{true}]$. However, applying this fix will violate c_2.

Existing work has proposed three different strategies to deal with this problem; each has its own advantages and disadvantages. We now revisit these three strategies, and show that they can all be used with range fix generation by converting a multi-constraint violation into a single-constraint one. In the evaluation section we will give a comparison of the three strategies.

Ignorance All constraints in C are simply ignored, and only fixes for (V, e, c) are generated. This strategy is used in fix generation approaches considering only one constraint [19]. This strategy does not solve the constraint interaction problem at all. However, it has its merits: first, the fixes are only related to the violated constraint, which makes it easier for the user to comprehend the relation between the fixes and the constraints; secondly, this strategy does not suffer from the problems of incomplete fix list and large fix list, unlike the two others; thirdly, this strategy requires the least computation effort and is the easiest to implement.

Elimination When a fix violates other satisfied constraints, it is excluded from the list of fixes, i.e., the fix is "eliminated" by other constraints. In the example in violation (2), fix r will violate c_2 and thus is excluded from the generated fix set. This strategy is proposed by Egyed et al. [20] and used in their UML fix generation tool.

To apply this strategy to range fix generation, we first find a subset of C that shares variables with c, then replace the variables not in c with their current values in e, and connect all constraints by conjunctions. For example, to apply the elimination strategy to violation (2), we first find the constraints sharing variables with c, which includes only $c2$, and then replace x and y in c_2 with their current values, getting $c'_2 = n \rightarrow \texttt{false} \vee \texttt{false}$. Then we generate fixes for $(V, e, c \wedge c'_2)$.

Although the elimination strategy prevents the violation of new constraints, it has two noticeable drawbacks. First, it exudes many potentially useful fixes. In many cases, it is inevitable to bring new errors during error resolution. Simply excluding fixes will only provide less help to the user. In our example, we will get an empty fix set, which does not help the user resolve the error. Secondly, since we need to deal with the conjunction of several constraints, the resulting constraint is much more complex than the original one. Our evaluation showed that some conjunctions can count more than ten constraints. Nevertheless, compared to the propagation strategy, this increase in complexity is still small.

Propagation When a fix violates other constraints, we further modify variables in the violated constraints to keep these constraints satisfied. In this case, the fix is "propagated" through other constraints. For example, fix r will violate c_2, so we further modify variables x or y to satisfy c_2. Then the modification of x will violate c_3, and we further modify z. In the end, we get two fixes $[n := \texttt{true}, x := \texttt{true}, z := \texttt{true}]$ and $[n := \texttt{true}, y := \texttt{true}]$. This approach is used in the eCos configuration tool [15] and the feature model diagnosis approach proposed by White et al. [11].

To apply this strategy, we first perform a static slicing on C to get a set of constraints directly or indirectly related to c. More concretely, we start from a set D containing only c. If a constraint c' shares any variable with any constraint in D, we add c' to D. We keep adding constraints until we reach a fixed point. Then we make a conjunction of all constraints in D, and generate fixes for the conjunction. For example, if we want to apply the propagation strategy to violation (2), we start with $D = \{c\}$, then we add c_2 because it shares n with c, next we add c_3 because it shares x with c_2. Now we reach a fixed point. Finally, we generate fixes for $(V, e, c \wedge c_2 \wedge c_3)$.

The propagation strategy ensures that no satisfied constraint is violated and no fix is eliminated. However, there are two new problems. First, the performance cost is the highest among the three strategies. The constraints in real-world models are highly interrelated. In large models, the strategy often led to conjunctions of hundreds of constraints. The complexity of analyzing such large conjunctions is significantly higher than analyzing a single constraint. Secondly, since many constraints are considered together, this strategy potentially leads to large fixes (i.e., fixes that modify a large set of variables), and large number of fixes, which are not easy to read and to apply.

V. Implementation

We have implemented a command-line tool generating fixes for eCos CDL using the Microsoft Z3 SMT solver [14]. Our tool takes a CDL configuration as input, and automatically generates fixes for each configuration error found. Alternatively, the user can enter an option to activate via the command-line interface, and our tool generates fixes to activate this option.

To implement our algorithm, one important step is to convert the constraint in the CDL model into the standard input format of the SMT solver: SMT-LIB [21]. To perform this task, we carefully studied the formal semantics of CDL [17], [22] through reverse engineering from the configurators and the documents. However, there are still two problems to deal with. First, CDL is an untyped language, while SMT-LIB is a typed language. To convert CDL, we implement a type inference algorithm to infer the types of the options based on their uses. When a unique type cannot be inferred or type conflicts occur, we manually decide the feature types.

The second problem is dealing with string constraints. The satisfiability problem of string constraints is undecidable in general [18], and general SMT solvers do not support string constraints [14]. Yet, string constraints are heavily used in CDL models. Nevertheless, our previous study on CDL constraints [9] actually shows that the string constraints used in real world models employ a set semantics: a string is considered as a set of substrings separated by spaces, and string functions are actually set operations. For example, `is_substr` is actually a set member test. Based on this discovery, we encode each string as a bit vector, where each bit indicate a particular substring is presented or not. Since in fix generation we will never need to introduce new substrings, the size of the bit vector is always finite and can be determined by collecting all substrings in the model and the current configuration.

VI. Evaluation

A. Methodology

Our algorithm ensures Properties 1-4 for the generated range fixes. However, to really know whether the approach works in practice, several research questions need to be answered by empirical evaluation:

- **RQ1**: How complex are the generated fix lists?
- **RQ2**: How often are the final user changes covered by our fixes?
- **RQ3**: How efficient is our algorithm?
- **RQ4**: Does our approach cover more user changes than existing approaches?
- **RQ5**: What are the differences among the three strategies?

The evaluation uses 6 eCos configuration files from 5 eCos-based open-source projects (Table I). Each file targets a different hardware architecture (the first column in Table I); each architecture uses a different mixture of eCos packages, yielding variability models with different options and constraints (columns three and four). The configuration process for a given model starts from the model's default configuration; the last column in Table I specifies the number of changes made by a project to a default configuration.

Table I: Real World Configuration Files

Architecture	Project	Options	Constraints	Changes
virtex4	ReconOS	933	330	49
xilinx	ReconOS	765	272	53
ea2468	redboot4lpc	658	96	14
aki3068net	Talktic	817	195	3
gps4020	PSAS	535	85	23
arcom-viper	libcyt	771	189	26

Table II: Constraint violations

Architecture	Erros in defaults	Errors in changes	Activating
virtex4	56	5	15
xilinx	48	1	2
ea2468	8	8	1
aki3068net	26	3	0
gps4020	12	10	4
arcom-viper	26	0	0

The evaluation needs a set of real-world constraint violations. Interestingly, the default configuration for each model already contains *errors*—violations of requires constraints. The first column in Table II shows their numbers. The models share common core packages, causing duplicated errors. A set of 68 errors from defaults remain after removing duplicates.

For RQ2 and RQ4, we attempt to recover the sequence of user changes from the revision history of the configuration files. We assume that the user starts from the default configuration and solves errors from defaults by accepting the suggestions from the eCos configurator. We record this corrected default configuration as the first version. Then we diff each pair of consecutive revisions to find changes to options. Next we replay these changes to simulate the real configuration process. Since we do not know the order of changes within a revision, we use three orders: a top-down exploration of the configuration file, a bottom-up one, and a random one. The rationale for the first two orders is that expert users usually edit the textual configuration file directly rather than using the graphical configurator. In this case, they will read the options in the order that they appear in the file, or the inverse if they scroll from bottom to top.

We replay the changes as just explained and collect (i) errors—violating requires constraints—and (ii) *activation violations*. An activation violation occurs when an option value should be changed, but is currently inactive. The last two columns in Table II show the numbers of the resulting violations from changes. After duplicate removal, 27 errors and 22 activation violations remain; together with the first

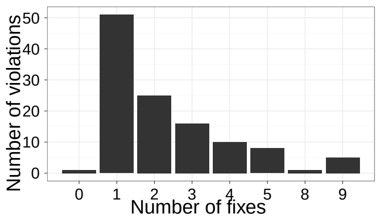


Figure 5: The number of fixes per violation

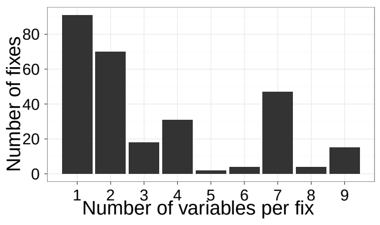


Figure 6: The number of variables per fix

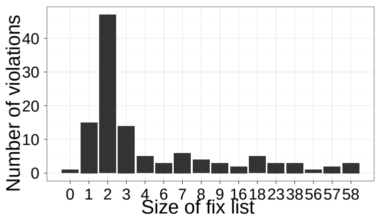


Figure 7: The sizes of fix lists

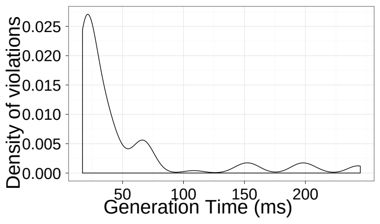


Figure 8: Fix generation time

dataset, we have a total of 117 multi-constraint violations.

Finally, we invoke our tool to generate fixes for the 117 violations. For RQ4, we also invoke the built-in fix generator of the eCos configurator on the 27 errors from the user changes. The activation violations are not compared because they are not supported by the eCos configurator. The experiments were executed on computer with Intel Core i5 2.4 GHz CPU and 4 GB memory.

B. *Results*

We first give the results for RQ1-RQ4 using the propagation strategy. We answer RQ5 by presenting the comparison of the three strategies last.

RQ1 To answer RQ1, we first consider two basic measures over the 117 violations: the distribution of the number of fixes per violation (see Figure 5) and the distribution of the number of variables changed by each fix (see Figure 6). From these figures we see that most fix lists are short and most fixes change a small number of variables. More concretely, 95% of the fix lists contain at most five fixes and 75% of the fixes change less than five variables. There is also an activation violation that did not produce any fix. A deeper investigation of this violation revealed that the option is not supported by the current hardware architecture, and cannot be activated without introducing new configuration errors. The extracted changes actually lead to an unsolved configuration error in the subsequent version.

It is still unclear how the combination of fix number and fix size affect the size of a fix list, and how the large fixes and long lists are distributed in the violations. To understand this, we measure the size of a fix list. The size of a fix list is defined as the sum of the number of variables in each fix. The result is shown in Figure 7. From the figure we can see that the propagation strategy does lead to large fix lists. The largest involves 58 variables, which is not easily readable. However, the long lists and large fixes tend to appear only on a relatively few number of violations, and the majority of the fix lists are still small: 83% of the violations contains less than 10 variables.

We also measure the number of variables in each fix unit to understand how large the fix units are. It turns out that every fix unit contains only one variable. This shows that (1) "minimality of fix units" effectively holds on all the violations and (2) ranges declared on more than one variable (such as the second fix for violation (1)) have never appeared in the evaluation.

RQ2 Given an error or activation violation, we examined the change history to identify a subsequent configuration that corrected the problem. To answer RQ2, we checked if the values in the corrected configuration fell within one of the ranges proposed by our generated fixes.

There are in total 47 out of 49 violations with subsequent corrections in our dataset. The fixes generated by our tool covered 46 of these violations (98%). An investigation into the remaining violations showed that the erroneous option discussed in RQ1 is responsible for that discrepancy. Since the propagation strategy ensures no new error is introduced, the resolved value from the dataset was not proposed as a fix.

RQ3 For each of the 117 violation, we invoked the fix generator 100 times, and calculated the average time. The result is presented as a density graph in Figure 8. It shows that most fixes are generated within 100 ms. Some fixes require about 200 ms, which is still acceptable for interactive tools.

RQ4 We measure whether the fixes proposed by the eCos configurator cover the user changes in the same way as in

RQ2. Since the eCos configurator is unable to handle the activation violations, we measure only error resolutions. There are 26 out of 27 errors that have subsequent corrections. The eCos configurator was able to handle 19 of the 26 errors, giving a coverage of 73%. Comparatively, our tool covered all 26 errors.

RQ5 As discussed in Section IV, the propagation strategy potentially produces large fix lists. At this stage, we would like to know if the other two strategies actually produce simpler fixes. We compare the size of fix lists generated by the three strategies in Figure 9. The elimination and ignorance strategies completely avoid large fix lists, with the largest fix list containing four variables in total. The elimination strategy changes even fewer variables because some of the larger fixes are eliminated.

We also compare the generation time of the three strategies. For all violations, the average generation time for the propagation strategy is 50ms, while the elimination strategy is 20ms and the ignorance strategy is 17ms. Since the overall generation time is small, it does not make a big difference in tooling.

Next, we want to understand to what extent the other two strategies affect completeness or bring new errors. First we see that the elimination strategy does not generate fixes for 17 violations. This is significantly more than the ignorance and propagation strategies, which have zero and one violation, respectively. We measure the coverage of user changes using the elimination strategy. In the 47 violations, only 27 are covered, giving a coverage of 57%. This is even lower than the eCos configurator, which generates only one fix, showing that a lot of useful fixes were eliminated by this strategy.

The problem of the ignorance strategy is that it may bring new errors. To see how frequently a fix brings new errors, we compare the fix list of the ignorance strategy with the fix list of the elimination strategy. If a fix does not appear in the list of elimination strategy, it must potentially bring new errors. As a result, 32% of the fixes generated by the ignorance strategy bring new errors, which covers 44% of the constraint violations. This shows that the constraints in practice are usually inter-related and the ignorance strategy potentially causes new errors in many cases.

VII. Threats to Validity

We see two main threats to external validity. First, we have evaluated our approach on one variability language. However, Berger et al. [2] study and compare three variability languages—CDL, Kconfig and feature modeling—and find that CDL has the most complex constructs for declaring constraints, and constraints in CDL models are significantly more complex than those in Kconfig models. Thus, our result is probably generalizable to the other two other languages.

The second threat is that our evaluation is a simulation rather than actual configuration process. We address this threat by using the models of six architectures and configurations gathered from five projects. The configurations and changes have a wide range of characteristics as shown in Tables I and II. However, it still may be that these changes are not representative of the problems that real users encountered. We hope to address this threat by running a user study in an industry setting in the future.

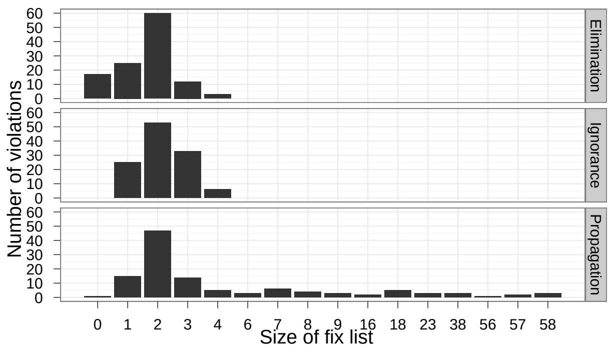


Figure 9: The sizes of fix lists in the three strategies

A threat to internal validity is that our translation of CDL into logic constraints could be incorrect. To address this threat, we have developed a formal specification of CDL semantics in functional style, in addition to the one developed by Berger et al. [17]. We have carefully inspected and compared both against each other and tested them on examples with respect to the eCos configurator.

VIII. Related Work

The idea of automatic fix generation is not new. Nentwich et al. [19] propose an approach that generates abstract fixes from first-order logic rules. Their fixes are abstract because they only specify the variables to change and trust the user to chose a correct value. In contrast, our approach also gives the range of values for a variable. Furthermore, their approach only supports "$=$" and "$\neq$" as predicates and, thereby, cannot handle models like eCos. Scheffczyk et al. [23] enhance Nentwich et al.'s approach by generating concrete fixes. However, this approach requires manually writing fix generation procedures for each predicate used in each constraint, which is not suitable for variability models, often containing hundreds of constraints. Egyed et al. [20] propose to write such procedures for each type of variable rather than each constraint to reduce the amount of code written and apply this idea to UML fix generation. Yet, in variability models, the number of variables is often larger than the number of constraints. The actual reduction of code is thus not clear. Jose et al. [10] generate fixes for programming bugs. They first identify the potentially flawed statements using MAXSAT analysis, and then propose fixes based heuristic rules. However, their heuristic rules are specific to programming languages and are not easily applicable to software configuration. Also, they propose at most one fix each time rather than a complete list.

Fix generation approaches for variability models also exist. The eCos configurator [15] has an internal fix generator, producing fixes for a selected error or on-the-fly when the user changes the configuration. White et al. [11] propose an approach to generate fixes that resolve all errors in one step. However, both approaches can only produce one fix rather than a complete list. Furthermore, they have very limited support of non-Boolean constraints. White et al.'s approach does not handle non-Boolean constraints at all, while eCos configurator supports only non-Boolean constraints in a simple form: $v \oplus c$ where v is a variable, c is a constant and $\oplus$ is an equality or inequality operator.

Another set of approaches maintain the consistency of a configuration. Valid domains computation [24], [25] is an approach that propagates decisions automatically. Initially all options are set to an unknown state. When the user assigns a value to an option, it is recorded as a decision, and all other options whose values are determined by this decision are automatically set. In this way, no error can be introduced. Janota et al. [26] propose an approach to complete a partial configuration by automatically setting the unknown options in a safe way. However, both approaches require that the configuration starts with variables in the unknown state. Software configuration in practice is often "reconfiguration" [2], i.e., the user starts with a default configuration, and then makes change to it. In reconfiguration cases, variables have assigned concrete values rather than the unknown state. Furthermore, these approaches are designed for small finite domains, and it is not clear whether they are scalable to large domains such as integers.

Several approaches have been proposed to test and debug the construction of variability models themselves. Trinidad et al. [27] use Reiter's theory of diagnosis [12] to detect several types of deficiencies in FODA feature models. Wang et al. [28] automatically fix deficiencies based on the priority assigned to constraints. These approaches target the construction of variability models and cannot be easily migrated to configuration.

Others automatically fix errors without user intervention. Demsky and Rinard [29] propose an approach to fix runtime data structure errors according to the constraint on the data structure. Mani et al. [30] use the hidden constraints in a transformation program to fix input model faults. Xiong et al. [31] propose a language to construct an error-fixing program consistently and concisely. Compared to our approach, these approaches also infer fixes from constraints, but they only need to generate one fix that is automatically applied. Completeness is not considered by these approaches.

The HS-DAG algorithm is often used in combination with the QuickXPlain algorithm [32]. The QuickXPlain algorithm computes the preferred explanations and relaxations for over-constrained problems. This combination has been successfully applied in recommender systems to find the most representative relaxations of a set of requirements, i.e., those with highest likelihood of being chosen by the users [33]–[35]. O'Sullivan et al. [36] propose an alternative algorithm for the same problem. The most representative relaxations are then used to propose alternative solutions based on a database of known operational solutions. The filtering of fixes is a possible extension to our work.

IX. Conclusion and future work

Range fixes provide alternative solutions to constraint violations in software configuration. They are correct, minimal in the number of variables per fix, maximal in their ranges, and complete. We also evaluated three different strategies for handling the interaction of constraints: ignorance, elimination, and propagation. On our data set, the propagation strategy provides the most complete fix lists without introducing new errors, and the fix sizes and generation times are within acceptable ranges. However, if more complex situations are encountered, elimination or ignorance can provide simpler fix lists and faster generation time, at the expense of completeness or the guarantee not to introduce new errors.

We are also implementing a new Kconfig configurator with range fix support. In addition, our industry partner has shown interest in including range fixes in their tool, and we are discussing the evaluation of our approach on large-scale industrial models and configurations.

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