Adaptive Testing for Specification Coverage

Ezio Bartocci¹, Roderick Bloem², Benedikt Maderbacher², Niveditha Manjunath¹,³, and Dejan Ničković²

¹ Vienna University of Technology
² Graz University of Technology
³ AIT Austrian Institute of Technology

Abstract. Ensuring correctness of cyber-physical systems (CPS) is an extremely challenging task that is in practice often addressed with simulation based testing. Formal specification languages, such as Signal Temporal Logic (STL), are used to mathematically express CPS requirements and thus render the simulation activity more systematic and principled. We propose a novel method for adaptive generation of tests with specification coverage for STL. To achieve this goal, we devise cooperative reachability games that we combine with numerical optimization to create tests that explore the system in a way that exercise various parts of the specification. To the best of our knowledge our approach is the first adaptive testing approach that can be applied directly to MATLAB™ Simulink/Stateflow models. We implemented our approach in a prototype tool and evaluated it on several illustrating examples and a case study from the avionics domain, demonstrating the effectiveness of adaptive testing to (1) incrementally build a test case that reaches a test objective, (2) generate a test suite that increases the specification coverage, and (3) infer what part of the specification is actually implemented.

1 Introduction

Cyber-physical systems (CPS) are becoming ubiquitous in many aspects of our lives. CPS applications combine computational and physical components and operate in sophisticated and unpredictable environments. With the recent rise of artificial intelligence and machine learning, CPS are becoming more and more complex and ensuring their safe operation is an extremely challenging task [25]. Despite tremendous progress in the past decade, formal verification of CPS still suffers from scalability issues and is not an option for analysing realistic systems of high size and complexity.

The onerous exhaustive verification of CPS designs is in practice often replaced by more pragmatic simulation-based testing [8]. This a-priori ad-hoc activity can be made more systematic and rigorous by enriching automated test generation with formal specifications. Signal Temporal Logic (STL) [23] is a popular specification language for expressing properties of CPS. STL admits robustness semantics [15] that allows measuring how far is an observed behavior from violating a specification. Falsification-based testing [29,14,11,15,21,20,11] is a method that uses robustness evaluation to guide the system-under-test (SUT)
to the specification violation. This successful testing approach provides effective means to detect bugs in CPS designs, but in case that no violation witness is detected, this method gives little information about design correctness. In addition, falsification testing typically stops upon detection of the first violation, thus reporting at most one fault at a time. The confidence in the design correctness can be achieved by introducing a notion of coverage to the testing activity – the design is considered to be correct if it passes all tests in a test suite that covers a sufficient number and variety of tests according to the chosen coverage metric.

We propose a novel adaptive test methodology for generating tests with specification coverage [27]. Intuitively, a test suite covers a specification if each requirement formalized in the specification is exercised by at least one test in the suite in a meaningful way. The overview of our approach is shown in Figure 1. We start with system requirements formalized in a variant of STL [17] that distinguishes input variables (controlled by the tester) from output variables (controlled by the SUT). We translate a STL specification to an equivalent symbolic automaton. We then define coverage on the symbolic automaton as well as the test goals needed to achieve this coverage. To reach a test goal, we formulate a cooperative reachability game that is played between the tester and the system. The goal of the game is for the tester to bring the SUT to a given state. The principle of cooperative games is that the two players are not necessarily adversarial to each other. The state-space of the game is partitioned into three zones: a safe zone in which we can advance the game without cooperation from the opponent, a no-hope zone from which we cannot advance the game regardless of the opponent moves, and a possibly winning zone from which we can advance the game if the opponent is willing to cooperate. The outcome of this game is a cooperative strategy. In order to execute this strategy when in a possibly winning zone, the tester needs to steer the SUT to select a move that allows advancing the game. We call this part of the procedure an adaptive step and formulate the problem of guiding the cooperative SUT move as an optimization
problem in which we use particle swarm optimization (PSO) [22] to efficiently direct the SUT behavior in a desired direction. The outcome of this activity is a set of test cases, one of which reaches the test goal. We use these test cases to measure coverage and define the next test goal. We repeat this process until we reach the desired level of coverage or until we have used the maximum number of simulations. We implement our approach in a prototype tool and evaluate it on several examples, including a case study with a Simulink model of an aircraft elevator control system. We demonstrate the effectiveness of adaptive testing to efficiently generate test cases that reach test objectives and increase specification coverage.

We summarize the main contribution of the paper:

- **Specification coverage:** we propose a new notion of coverage for STL specifications.
- **Testing methodology:** we develop a novel adaptive testing methodology that combines cooperative games with numerical optimization:
  - **Test case generation:** incremental generation of individual test cases that achieve a given objective, and
  - **Test suite generation:** steering of system executions that systematically increases specification coverage.
- **Implementation:** we implement the proposed method in a prototype tool and evaluate it on a case study from the avionics domain.

2 Related

**Fault-based testing.** Fault-based testing [20] consists in introducing a fault in a system implementation and then computing the test that can detect/reject it. A typical example is mutation testing where the modification of the original implementation is called *mutant*. The tests causing a different behavior of the mutant with respect to the original implementation are said to *kill the mutant*. The coverage of the test suite is measured by the percentage of mutants that can be killed. Our approach is complementary to fault-based testing. However, our notion of coverage measures the percentage of the states/transitions visited (during testing) of a symbolic automata generated from a Signal Temporal Logic (STL) [23] requirement with input/output signature.

**Falsification-based testing.** Falsification-based testing [29][11][15][24][6][26][11] is a well-established technique to generate tests violating requirements for CPSS models. This approach consists in exercising the model with different input sequences and by monitoring each simulation trace with respect to an STL [23] requirement. The use of STL quantitative semantics [15] is key to provide an indication as how far the trace is from violating the requirement. The quantitative interpretation can be employed as a fitness function for meta-heuristic optimization algorithms (e.g., ant colony optimization, simulating annealing, etc.) to guide the search of the input sequences violating the requirement. Although falsification-based testing has proven to be effective in many practical applications, the focus of this approach is solely on finding a bug and hence does not
attent increasing coverage. It also remains in general agnostic to the syntactic and semantic structure of STL specification. Our approach exploits instead the structure of the symbolic automaton generated from the STL requirement that we want to test and it develops a strategy to generate tests that increase the specification coverage.

**Model-based testing.** In model-based testing [16,3,2,28,13] a model of the desired behavior of the system under test is exploited to derive the testing strategies. The coverage is measured in terms of the percentage of the model’s components visited during testing. Our approach belongs to this class of testing methods, where the model is the symbolic automata generated from an STL requirement and the test cases are generated as winning strategies of a cooperative reachability game.

**Adapting testing.** Adaptive testing [9,10,2] require the test cases to adapt with respect to the SUT behavior observed at runtime in order to achieve the goal. This is particularly important when the SUT are reactive systems interacting with their environment. Our approach is also adaptive (see Figure 1), because it requires to simulate and monitor the SUT in order to optimize the input that tester should provide at each time step to find the winning strategy.

**Testing as a game.** As Yannakakis formulated first in [30], testing can be seen as game between a tester that aims to find the inputs revealing the faults in the system under test (SUT) and the SUT producing outputs while hiding the internal behavior. In [12] the authors presents a game-theoretic approach to the testing of real-time systems. They model the systems as Timed I/O Game Automata and they specify the test purposes as Timed CTL formulas. Using the timed game solver UPPAAL-TIGA they are able to synthesize winning strategies used to conduct black-box conformance testing of the systems. While in the context of timed automata, the game-theoretic approach is well-explored (see also the work of [19]), to the best of our knowledge our approach is the first that can be applied directly to MATLAB™ Simulink/Stateflow models.

**Property-based coverage.** In [27], the authors introduce the notion of property-based coverage metric for linear temporal logic (LTL) specificationa. Their approach operates on the syntax tree of the LTL specification. The metric, based on requirement mutation, measures how well a property has been tested by a test-suite by checking the subformulae of the LTL requirement covered by a set of tests. The main differences with our approach is the specification language (we use STL instead of LTL) and the use of the symbolic automata generated from the specification both for measuring the coverage and for generating tests using cooperative games.

### 3 Background

In this section, we recall the background that we use to build our adaptive testing approach. We define signals and systems, interface-aware Signal Temporal Logic, symbolic automata and provide a short overview of coverage criteria.
3.1 Signals and Systems

Let $X = \{x_1, \ldots, x_m\}$ be a finite set of real-valued variables. A valuation $v : X \rightarrow \mathbb{R}$ for $x \in X$ maps a variable $x \in X$ to a real value. Given two disjoint sets of variables $X_1$ and $X_2$ and their associated valuation mappings $v_1 : X_1 \rightarrow \mathbb{R}$ and $v_2 : X_2 \rightarrow \mathbb{R}$, we denote by $v = v_1 \parallel v_2$ valuation composition $v : (X_1 \cup X_2) \rightarrow \mathbb{R}$ such that $v(x) = v_1(x)$ if $x \in X_1$, and $v(x) = v_2(x)$ otherwise. A signal $v$ is a sequence $v_1, v_2, \ldots, v_n$ of valuations over $X$. We denote by $|v| = n$ the length of signal $v$.

Let $X_I$ be a set of input and $X_O$ a set of output variables. We consider non-linear discrete-time systems and assume that such a system $S$ is given in the form of a set of difference equations.

Example 1. Let $a, b \in X_I$ be input variables and $c, d \in X_O$ output variables. We define two simple stateless systems $S_1$ and $S_2$ over $X_I \cup X_O$:

$$
\begin{align*}
S_1 : c(t) &= a(t) \\
        d(t) &= a(t) + b(t) + 2 \\
S_2 : c(t) &= 2a(t) + b(t) \\
        d(t) &= a(t) + 10 - b(t)
\end{align*}
$$

3.2 Interface-Aware Signal Temporal Logic

We consider Signal Temporal Logic (STL) with inputs and outputs, past and future operators, quantitative semantics and interpreted over discrete time. An interface-aware signal temporal logic (IA-STL) specification $\phi$ over $X$ is a tuple $(X_I, X_O, \phi)$, where $X_I, X_O \subseteq X$, $X_I \cap X_O = \emptyset$, $X_I \cup X_O = X$ and $\phi$ is an STL formula. The syntax of a STL formula $\phi$ over $X$ is defined by the following grammar:

$$
\varphi := f(Y) \sim c \ | \ \neg \varphi \ | \ \varphi_1 \lor \varphi_2 \ | \ \varphi_1 U I \varphi_2 \ | \ \varphi_1 S I \varphi_2
$$

where $Y \subseteq X$, $\sim \in \{<, \leq\}$, $c \in \mathbb{R}$ and $I$ is of the form $[a, b]$ or $[a, \infty)$ such that $a$ and $b$ are in $\mathbb{N}$ and $0 \leq a \leq b$.

We equip IA-STL with standard quantitative semantics using the notion of robustness. Let $\varphi$ be an STL formula and $w$ a signal trace. We define the

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1 Given $x \in X$, we will abuse notation and denote by $x_i$ the valuation $v_i(x)$ projected to $x$ whenever it is clear from the context.
robustness $\rho(\varphi, w, t)$ by induction as follows:

\[
\begin{align*}
\rho(\text{true}, w, t) &= +\infty \\
\rho(f(Y) > 0, w, t) &= f(w_Y[t]) \\
\rho(\neg \varphi, w, t) &= -\rho(\varphi, w, t) \\
\rho(\varphi_1 \lor \varphi_2, w, t) &= \max\{\rho(\varphi_1, w, t), \rho(\varphi_2, w, t)\} \\
\rho(\varphi_1 U I \varphi_2, w, t) &= \sup_{t' \in (t \oplus I) \cap T} \min\left\{\rho(\varphi_2, w, t'), \inf_{t'' \in (t', t)} \rho(\varphi_1, w, t'')\right\} \\
\rho(\varphi_1 S I \varphi_2, w, t) &= \sup_{t' \in (t \ominus I) \cap T} \min\left\{\rho(\varphi_2, w, t'), \inf_{t'' \in (t', t)} \rho(\varphi_1, w, t'')\right\}
\end{align*}
\]

where $\oplus$ and $\ominus$ are Minkowski sum and difference, for all $a \in \mathbb{R}$, $\text{sign}(a) \cdot \infty = +\infty$ if $a > 0$, $-\infty$ otherwise. Other Boolean and temporal operators, such as implication ($\rightarrow$), always ($\Box I$), eventually ($\Diamond I$), historically ($\triangleleft I$) and once ($Q I$) are derived from the basic operators using the standard procedure.

**Example 2.** Let $\varphi = \{(a, b), \{c, d\}, \varphi\}$ be an IA-STL specification defined over input variables $a$ and $b$, and output variables $c$ and $d$. The specification states that every time $a$ is greater or equal to 4 for exactly two time units, either $b$ is negative and $c$ must be within one time unit greater or equal to 4, or $b$ is positive and $d$ must be greater or equal to 6 within one time unit.

$$\varphi = \Box(a \geq 4 \rightarrow ((b \leq 0 \land c \geq 4) \lor (b > 0 \land d \geq 6))$$

It is not hard to see that $S_1$ satisfies $\varphi$, while $S_2$ violates it. For instance, a witness of $S_2$ violating $\varphi$ is an input signal in which $a$ equals to 4 and $b$ is greater than 2.

### 3.3 Symbolic Automata

A metric space is a set $M$ possessing a distance $d$ among its elements and satisfying identity, symmetry and triangle inequality constraints. Given a set $M$, an element $m \in M$ and $M \subseteq M$, we can lift the definition of a distance to reason about the distance between an element $m$ of $M$ and the subset $M$ of $M$ to define a Hausdorff-like measure. In this extension, we extend the set of reals with the infinity $\infty$ element. We also need a special value when we compare $m$ to an empty set and define $d(m, \emptyset) = \infty$.

\[
d(m, M) = \begin{cases} 
\infty & \text{if } M \text{ is empty} \\
\min_{m' \in M} d(m, m') & \text{otherwise.}
\end{cases}
\]

Since $d(m, M)$ is comparing an element to a set, strictly speaking it is not a distance.
Definition 1 (Predicate). The following grammar defines the syntax of a predicate \( \psi \) over \( X \): 
\[
\psi := \top \mid f(Y) > 0 \mid \neg \psi \mid \psi_1 \lor \psi_2, \text{where } Y \subseteq X.
\]

\( \Psi(X) \) denotes all predicates over \( X \). We lift the definition of a distance between two valuations to the distance between a valuation and a predicate.

Definition 2 (Valuation-predicate distance). Given a valuation \( v \in V(X) \) and a predicate \( \psi \in \Psi(X) \), we have that:
\[
d(v, \psi) = \min_{v' = \psi} \max_{x \in X} d(v(x), v'(x)).
\]

We now define symbolic and symbolic weighted automata.

Definition 3 (Symbolic Automata). A symbolic automaton (SA) \( A \) is the tuple \( A = (X, Q, I, F, \Delta) \), where \( X \) is a finite set of variables partitioned into the disjoint sets \( X_I \) of input and \( X_O \) of output variables. \( Q \) is a finite set of locations, \( I \subseteq Q \) is the set of initial states, \( F \subseteq Q \) is the set of final states and \( \Delta \subseteq Q \times \Psi(X) \times Q \) is the transition relation.

A path \( \pi \) in \( A \) is a finite alternating sequence of locations and transitions \( \pi = q_0, \delta_1, q_1, \ldots, q_{n-1}, \delta_n, q_n \) such that \( q_0 \in I \) and for all \( 1 \leq i \leq n, (q_{i-1}, \delta_i, q_i) \in \Delta \). We say that the path \( \pi \) is accepting if \( q_n \in F \). We say that a signal \( w = v_1, v_2, \ldots, v_n \) induces a path \( \pi = q_0, \delta_1, q_1, \ldots, q_{n-1}, \delta_n, q_n \) in \( A \) if for all \( 1 \leq i \leq n, v_i \models \psi_i \), where \( \delta_i = (q_{i-1}, \psi_i, q_i) \). We denote by \( \Pi(w) = \{ \pi \mid \pi \in F \text{ and } w \text{ induces } \pi \text{ in } A \} \) the set of all accepting paths in \( A \) induced by trace \( w \).

A SA \( A \) is deterministic iff \( I = \{ q \} \) for some \( q \in Q \) and for all \( \delta = (q, \psi, q'), \delta' = (q, \psi', q'') \in \Delta \) such that \( \delta \neq \delta' \), \( \psi \land \psi' \) is unsatisfiable. A SA \( A \) is complete iff for all \( q \in Q, v \in V(X) \), there exists \( (q, \psi, q') \in \Delta \) such that \( v \models \psi \). Additionally we require all predicates to be satisfiable: \( \forall (q, \psi, q') \in \Delta : \exists v \in V(X) : v \models \psi \).

Example 3. Consider the IA-STL specification \( \phi \) from Example 2. Figure 2 depicts the deterministic symbolic automaton \( A_\phi \) associated with \( \phi \).

3.4 Specification Coverage

A test coverage criterion \( C \) defines a set of testing requirements that a test suite \( T \) must fulfill. Given a test \( \tau \in T \) and a requirement \( c \in C \), we denote by \( \tau \models c \) the fact that \( \tau \) satisfies the criterion \( c \). We define by \( R(\tau, C) = \{ c \mid c \in C \text{ and } \tau \models c \} \) and \( R(T, C) = \bigcup_{\tau \in T} R(\tau, C) \) the set of test coverage requirements from the criterion \( C \) satisfied by the test \( \tau \) and the test suite \( T \), respectively. The test coverage of \( T \), denoted by \( K(C, T) \), is the ratio between the number of testing requirements in \( C \) that \( T \) fulfills and the total number of testing requirements defined by \( C \), that is \( K(C, T) = \frac{|R(T, C)|}{|C|} \).

Test coverage criteria are typically defined on the finite state machine that specifies the intended behavior of the SUT (model-based or black-box testing).
or on the actual code of the SUT implementation (white-box testing). Test coverage metrics have been a vivid area of research. We focus in this paper on two simple criteria, defined on the symbolic automaton derived from the IA-STL specification – location and transition coverage criteria that we formally define in the remainder of this section.

Let \( \phi = (X_I, X_O, \varphi) \) be an IA-STL specification, \( A_\phi \) its associated symbolic automaton and \( S \) the system model. A test \( \tau \) is the sequence \( v_I \) of input variable valuations. The location coverage criterion \( C_Q = Q \) is the set of all locations in \( A_\phi \). Given a location \( q \in C_Q \) and a test \( \tau \), we have that \( \tau \) satisfies the criterion \( c \) if the input signal \( \tau \) induces a path \( \pi = q_0, \delta_1, \ldots, q_{n-1}, \delta_n, q_n \) and \( q = q_i \) for some \( i \in [0, n] \). Similarly, we define the transition coverage criterion \( C_\Delta = \Delta \) as the set of transitions in \( A_\phi \).

**Example 4.** Consider the system \( S_2 \) from Example 1, the IA-STL specification \( \phi \) from Example 2 and its associated symbolic automaton \( A_\phi \) from Example 3. Equation 1 shows the test suite \( T = \{ \tau_1, \tau_2 \} \) and the induced outputs \( S_2(\tau_1) \) and \( S_2(\tau_2) \). The trace \( \tau_1 \parallel S_2(\tau_1) \) induces the run \( s_0, t_0, s_0, t_1, s_1, t_2, s_2, t_{11}, s_0 \) in \( A_\phi \), while the test \( \tau_2 \parallel S_2(\tau_2) \) induces the run \( s_0, t_1, s_1, t_7, s_2, t_{11}, s_0 \) in \( A_\phi \).

![Fig. 2. Symbolic automaton \( A_\phi \).](image-url)
\begin{align*}
\tau_1 &: a: 3 4 3 \\
b: 2 2 2 \\
S_2(\tau_1): c: 8 10 8 \\
d: 11 12 11
\end{align*} 
\begin{align*}
\tau_2 &: a: 4 4 2 \\
b: 2 8 2 \\
S_2(\tau_2): c: 10 0 6 \\
d: 12 22 10
\end{align*} 

In this example, we have that \( R(\tau_1, C_Q) = \{s_0, s_1\} \), \( R(\tau_1, C_\Delta) = \{t_0, t_1, t_2\} \), \( R(\tau_2, C_Q) = \{s_0, s_1, s_2\} \) and \( R(\tau_2, C_\Delta) = \{t_1, t_7, t_{11}\} \). It follows that \( R(T, C_Q) = \{s_0, s_1, s_2\} \) and \( R(T, C_\Delta) = \{t_0, t_1, t_2, t_7, t_{11}\} \). Hence, these two test cases together achieve \( K(C_Q, T) = 60\% \) location and \( K(C_\Delta, T) = 36\% \) transition coverage.

### 3.5 Specification-based Testing as Optimization

The quantitative semantics of STL allows to formulate the testing problem of finding an input sequence that violates an IA-STL specification \( \phi \) as an optimization problem over the input sequence \( \tau \) as follows:

\[
\min_{\tau} \rho(w, \phi) \text{ s.t. } w = \tau \| S(\tau)
\]

This testing approach is also known as falsification testing in the literature. The optimization procedure can take multiple forms: gradient descent, genetic algorithms, simulated annealing, etc.

In this paper, we use particle swarm optimization (PSO) [21], a randomized search algorithm in which a collection of points in the search space are updated at each iteration to move closer (on average) to a global optimal solution. The PSO procedure is summarized in Algorithm 1. The PSO algorithm takes as input the IA-STL specification \( \phi \), the system model \( S \), the input space \( V(X_I) \), termination constant \( k \), and the PSO parameters \( (W, r_p, r_g, m) \), where \( W \) is the particle velocity scaling factor, \( r_p \) is the scaling factor to search away from the particle’s best known position, \( r_g \) is the scaling factor to search away from the swarm’s best known position and \( m \) is the number of particles. The function \( \eta(0, r) \) used by the algorithm represents a random number uniformly distributed over the interval \([0, r]\). We motivate the choice of PSO by the results presented in [7] where it was chosen due to its inherent distributed nature and its ability to operate on irregular search spaces. In particular, PSO does not require a differentiable objective function.

### 4 Adaptive Testing for Specification Coverage

In this section, we present the adaptive testing algorithm for specification coverage. We start by introducing cooperative reachability games in Section 4.1 and then present the adaptive testing algorithm that combines cooperative games with numerical optimization in Section 4.2.
Algorithm 1: Particle Swarm Optimization

Input: IA-STL specification $\phi = (X_I, X_O, \varphi)$, system model $S$, input space $V(X_I)$, PSO parameters ($W, r_p, r_g, m$), termination constant $k$

Output: Input sequence $\tau \in V(X_I)^*$

1. for $1 \leq i \leq m$
   2. $u_i \leftarrow$ initialize particle positions in the input space $V(X_I)$;
   3. $v_i \leftarrow$ initialize particle velocities;
4. end
5. while $V(X_I)^*$ has changed during the last $k$ iterations do
   6. $\tau \leftarrow$ draw an input for the system;
   7. $\omega \leftarrow$ simulate the model dynamics according to the input $\tau$;
   8. $\rho(\varphi, \tau \parallel \omega) \leftarrow$ calculate the quantitative semantics of $\tau \parallel \omega$ with respect to $\varphi$;
   9. $\tau_{best} \leftarrow \max(\tau_1, \ldots, \tau_m)$;
10. $v_i \leftarrow Wv_i + \eta(0, r_p)(\tau_{best} - \tau_i) + \eta(0, r_g)(\tau_{best} - \tau_i)$;
11. $\tau_i \leftarrow \tau_i + v_i$;
12. end

4.1 Cooperative Reachability Games

Cooperative reachability games have been used for testing by David et al. [12]. In the following we define our own version that allows cooperation at any point (not only at the beginning) and is also able to handle real valued signals.

A symbolic reachability game $G$ is the pair $(A, W)$ where $A$ is a deterministic symbolic automaton and $W \subseteq Q$ is a set of target locations. The game is played by two players, the tester and the system. In every location $q \in Q$ starting from the initial location $q_0$ the tester moves first by picking inputs $v_I \in V(X_I)$ and in response the system picks outputs $v_O \in V(X_O)$. An interaction in which both players take a move by choosing their values is called a turn. A game is won by the tester if at some point a target state $q_n \in W$ is reached.

A test strategy $\sigma : Q^* \rightarrow 2^{V(X_I)}$ is used to determine the values the tester picks in each move, based on the trace of previously visited locations. We generalize strategies to not only provide a single input for each move, but instead a set of possible inputs. In the following we will focus on positional strategies $\sigma : Q \rightarrow 2^{V(X_I)}$ where the next move only depends on the current location $q$. A strategy is called a winning strategy if a tester picking inputs according to the strategy is guaranteed to achieve the winning condition, independent of the systems choices.

The tester cannot expect to reach all location of the specification, if the system is adversarial, i.e., it tries to deny that. Instead, we assume a setting where the system may choose outputs that help the tester. We first give an informal overview and provide the formal definitions afterwards.

A strategy distinguishes three kinds of locations with respect to reaching the target set. A force location is one where the tester can pick inputs such that it is guaranteed to get to a location closer to the target set; a cooperative location...
A cooperative winning strategy is a strategy where a tester following it will always reach the target set if the system helps in all cooperative locations. We now give the formal definitions of a cooperative winning strategy and how it can be obtained from a game automaton.

To calculate a cooperative winning strategy for a game $G$ we first define the functions $f : Q \times 2^Q \to 2^{V(X_I)}$ and $c : Q \times 2^Q \to 2^{V(X_O)}$. The function $f$ takes a location $q$ and a set of locations $S$ and evaluates to the set of inputs that allow the tester to reach a location in $S$ from $q$ in a single turn, for all possible outputs of the system. Formally, we define $f(q, S) = \{ v_I \in V(X_I) \mid \forall v_O \in V(X_O) : \exists (q, \psi, q') \in \Delta : q' \in S \land v_I[v_O = \psi] \}$. The function $c$ is defined analogously, but assumes the system cooperates by existentially quantifying the outputs; $c(q, S) = \{ v_I \in V(X_I) \mid \exists v_O \in V(X_O) : \exists (q, \psi, q') \in \Delta : q' \in S \land v_I[v_O = \psi] \}$. We use two nested fixpoints to calculate the winning region, the set of all locations for which $W$ can be reached. The strategy should contain the least amount of cooperative steps possible. Therefore we only grow it by a cooperative move if we cannot grow it with a force move. The intermediate regions are sets indexed by two natural numbers, the first one counting the cooperative steps and the second one counting the force steps. We initialize $Y_{0,0} = W$. We extend a region by force moves such that $Y_{i,j+1} = Y_{i,j} \cup \text{pre}_{\text{force}}(Y_{i,j})$, till we reach a fixpoint $Y_{i,\infty} = \bigcup_j Y_{i,j}$. In that case we extend the set by a single cooperative move $Y_{i+1,0} = Y_{i,\infty} \cup \text{pre}_{\text{coop}}(Y_{i,\infty})$ and iterate these two steps until the fixpoint $Y_{\infty,\infty} = \bigcup_j Y_{i,\infty}$ is found. This process converges, as the number of states is finite. There exists a cooperative winning strategy iff the initial state $q_0$ is in the winning region $Y_{\infty,\infty}$.

A strategy can be extracted from this fixpoint calculation as follows. Let $r$ be a function mapping locations in the winning region to pairs $(i, j)$ of positive integers identifying the first (smallest) region $Y_{i,j}$ containing the location. Formally, $r(q) = (i, j)$ such that $q \in Y_{i,j}$, but $q \notin Y_{i',j'}$ for any $(i', j')$ lexicographically smaller than $(i, j)$ where $Y_{i,j}$ are sets from the fixpoint computation.

Let $\text{Force} = \{ q \mid r(q) = (i, j + 1) \}$ and $\text{Coop} = \{ q \mid r(q) = (i + 1, 0) \}$ be the sets of force and cooperative locations. Using these, the strategy function is defined as:

$$
\sigma(q) = \begin{cases} 
\emptyset & \text{if } q \notin Y_{\infty,\infty} \\
V(X_I) & \text{if } q \in Y_{0,0} \\
f(q, Y_{i,j}) & \text{if } q \in \text{Force} \text{ and } r(q) = (i, j + 1) \\
c(q, Y_{i,\infty}) & \text{if } q \in \text{Coop} \text{ and } r(q) = (i + 1, 0). 
\end{cases}
$$

is one where the tester can pick inputs such that it gets to a location closer to the target set iff the system chooses helpful outputs; a no-hope location is any one from where the target set can never be reached.
The good transitions according to the strategy, that is those pointing to the next smaller region either by force or cooperation, are given as:

$$\Delta_S = \{(q, \psi, q') \in \Delta \mid q \in \text{Force} \land r(q) = (i, j + 1) \land q' \in Y_{i,j}\} \cup \{(q, \psi, q') \in \Delta \mid q \in \text{Coop} \land r(q) = (i + 1, 0) \land q' \in Y_{i,\infty}\}.$$ 

The strategy automaton $S$ for a game $G$ is the tuple $S = (X, Y_{\infty,\infty}, \text{init}, \Delta_S, \text{Force}, \text{Coop}, W, \sigma)$. It is a subgraph of the automaton $A$ which only contains the states from the winning region $Y_{\infty,\infty}$ and the transitions defined as $\Delta_S$. There is unique initial state $\text{init}$. The states are partitioned into Force, Coop and target states $W$. Additionally, $\sigma$ labels each state with the set of good inputs.

**Example 5.** Consider the automaton $A_\phi$ from Example 3. The cooperative winning strategy for reaching the target state $s_4$ is depicted as the strategy automaton $S_\phi$ in Figure 3. The input set given by $\sigma$ is shown symbolically as a predicate on each state. Cooperative states are bold whereas the target state is dashed. The transition predicates are the same as in Figure 2. Additionally, the regions of the fixpoint computation used to obtain the strategy are shown.

### 4.2 Adaptive Testing with Cooperative Games and Search-based Testing

In Section 4.1, we presented a game between a tester and a system and developed a procedure for computing a cooperative strategy from this game that requires cooperation between the two players in order to reach the game objective. In this section, we propose a procedure based on PSO that facilitates the cooperation between the two players. We generalize this procedure to devise a method for adaptive testing with specification coverage.

The main procedure `adaptive_testing` is described in Algorithm 2. The procedure takes as inputs: (1) the automaton $A$ obtained from the specification $\phi$, (2) the system model $S$, and (3) the user-defined budget $N$ that defines the

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3 We assume location coverage when describing the procedure. However, the procedure can be adapted to transition coverage.
Algorithm 2: Algorithm adaptive_testing

Input: Specification automaton $A$, system $S$, budget $N$
Output: Test suite $T$, visited locations $R(C_Q,T)$

1 $R := \emptyset$; $T := \emptyset$;
2 while $R \subseteq Q \land N \geq 0$ do
3 \quad $\hat{q} := Q \setminus R$;
4 \quad $A' := A$;
5 \quad $b := false$;
6 \quad \quad while $\neg b \land N \geq 0$ do
7 \quad \quad \quad $S := \text{new}_S(A', \{\hat{q}\})$;
8 \quad \quad \quad $q = \text{init}(S)$;
9 \quad \quad \quad $b := \text{explore}_S(A', T, R, N, S, q, \hat{q}, [])$;
10 \quad \quad end
11 \quad end
12 return $(T, R)$;

maximum number of system model simulations. The procedure computes a test
suite $T$ and the set $R(C_Q,T)$ of test coverage requirements from the location
criterion $C_Q$ satisfied by $T$.

The procedure adaptive_testing maintains a set of generated input sequences
$T$ and a set of visited states $R$ that are both initialized to empty sets (line 1).
The main loop (lines 2 - 11) consists in generating tests that improve location
coverage of $A$. It is executed as long as the procedure has not visited all locations
in the automaton and the budget allows us to execute more simulations. In every
loop iteration, the procedure first selects a target location $\hat{q}$ that has not been
visited yet (line 3) and makes a copy of the input automaton $A$ into $A'$ (line 4).
In the next step, the algorithm attempts to generate a test that allows reaching
the target location. The procedure generates a cooperative reachability strategy
(see Section 4.1) $S$ from $A$ and $\hat{q}$ (line 7). The initial location of the strategy
automaton is copied to $q$ (line 8). The cooperative reachability strategy $S$ is
explored by the procedure explore. This procedure aims at generating an input
sequence, that when executed on the system model $S$, induces a run in $S$ that
reaches $\hat{q}$ from the initial location. If successful, the procedure returns true.
Otherwise, it returns false and updates the automaton $A'$. The automaton $A'$ by
removing the location that could not be reached and that is used to generate a
new cooperative strategy. In both cases, the procedure updates the set $T$ with
input sequences used to simulate the system model $S$, the set $R$ with the set
of locations that were visited by runs induced by these input sequences and the
remaining budget $N$. Algorithm\textsuperscript{4} describes the details of the procedure explore.

The procedure explore aims at executing a cooperative strategy by using
PSO to facilitate cooperation between the tester and the system. This procedure
recursively computes the test input sequence $\tau$ that induces a run from an initial

\textsuperscript{4} We assume that explore passes parameters by reference. In particular, the procedure
updates $A'$, $T$, $R$ and $N$.}
Algorithm 3: Algorithm $\text{explore}_S$

**Input:** Automaton $A$, input sequences $T$, visited locations $R$, budget $N$, system $S$, initial location $q$, input prefix $\tau$

**Output:** Flag $b$

1. $R := R \cup \{q\}$;
2. if $q = \hat{q}$ then return true;
3. end
4. if $q \in \text{Force}$ then
5. in $\in \sigma(q)$;
6. $\tau := [\tau, \text{in}]$; $T := T \cup \{\tau\}$;
7. $\omega := \text{simulate}(S, \tau)$;
8. $N := N - 1$;
9. val := last($\tau$) || last($\omega$);
10. $q' := \{s \mid (q, \psi, s) \in \Delta_S \text{ and } \text{val} \models \psi\}$;
11. return $\text{explore}_S(A', T, R, N, S, q', \hat{q}, \tau)$;
12. end
13. else
14. for $(q, \psi, q') \in \Delta_S$ do
15. (in, b) := $\text{psol}(\psi, S, N)$;
16. if b then
17. $\tau := [\tau, \text{in}]$;
18. $T := T \cup \{\tau\}$;
19. $R := R \cup \{q'\}$;
20. return $\text{explore}_S(A', T, R, N, S, q', \hat{q}, \tau)$;
21. end
22. else
23. $A' := (X, Q, I, F, \Delta \setminus \{(q, \psi, q')\})$;
24. return false;
25. end
26. end
27. end
28. end

location $q$ to the target location $\hat{q}$. It first adds the input location $q$ into the set of visited states (line 1). It then checks if $q$ is the target state, and if yes, it returns true. Otherwise, the procedure checks if the location $q$ is of type Force or Cooperative.

If the location $q$ is a forced location (lines 5 – 13), the algorithm first finds an input that satisfies the input predicate associated to $q$ (line 6) by invoking an SMT solver and finding a model of the formula representing the input predicate. This input is appended to the existing input sequence and is added to the test suite $T$ (line 7). Next, the system model $S$ is simulated with $\tau$ (line 8) and the remaining simulation budget is decremented by one (line 9). The procedure then picks the target location $q'$ of the transition whose predicate is satisfied by the computed input/output valuation from the simulation (line 11), and the
procedure reinvokes itself, but with \( q' \) as the new input location and with the updated other parameters. If the location \( q \) is Coop (lines 14 – 28), then the algorithm repeats an exploration step for each of its outgoing transitions (lines 15 – 27). The procedure tries to find a valuation that satisfies the predicate \( \psi \) that decorates the transition. It does so by invoking the particle swarm optimization (PSO) procedure. We deviate from the standard PSO, described in Algorithm 1, by adding two adaptations to the procedure: (1) it stops as soon as it finds a valuation that satisfies the predicate \( \psi \) and enables the transition, and (2) after each simulation, it decrements the budget variable \( N \) by one and terminates if the entire budget is consumed. Every step of the PSO search invokes a simulation of the system model with the input chosen by the PSO algorithm. If the search for the valuation that enables the transition is successful (lines 17 – 22), then the procedure reinvokes itself with the target location \( q' \) of the transition. Otherwise, the procedure updates the automaton \( A' \) by removing the transition \( (q, \psi, q') \) and returns false (lines 23 – 26).

5 Evaluation and Experiments

In this section, we evaluate our approach and present experimental results. We first illustrate the outcomes of adaptive testing on the illustrative example used in the paper. We then apply and evaluate the adaptive testing procedure on an Aircraft Elevator Control System case study.

5.1 Evaluation using the Illustrative Example

In this section, we illustrate qualitative outcomes of adaptive testing applied to the systems \( S_1 \) and \( S_2 \) from Example 1 with the formal specification \( \varphi \) of its requirements from Example 2.

We first apply adaptive testing to \( S_1 \). We do not set an upper bound on budget and we initialize the PSO algorithm with the maximum swarm size of 100 and the maximum number of iterations of 100. Adaptive testing procedure conducted 390 simulations in 57s (including 10s for initializing MATLAB Simulink). The results of this experiment are shown in Figure 4. This figure depicts the specification coverage for \( S_1 \) and \( \varphi \). Visited locations and transitions are shown in green. We used red color to mark locations and transitions that could not be reached. Every visited location and transition is labeled by the number of times it was visited.

We can make the following observations. First, we could achieve 40% location and 38% transition coverage. While this coverage may seem low, it actually cannot be improved for two reasons: (1) \( S_1 \) satisfies \( \varphi \), hence the error location \( s_4 \) cannot be reached and its incoming transitions \( t_9, t_{10} \) and \( t_{13} \) of \( s_4 \) cannot be enabled by any input/output combination allowed by the dynamics of \( S_1 \); and (2) \( S_1 \) implements only a subset of \( \varphi \) (implementation choice). For instance, \( S_1 \) always immediately satisfies the obligation \( \Diamond_{[0,1]} c \geq 4 \) in \( \varphi \) even though the
specification allows satisfying it with one-step delay. As a consequence, adaptive testing does not only gives us confidence that $S_1$ satisfies $\varphi$, it also indicates which implementation choices were made. In particular, we can observe that the green locations and transitions from Figure 4 corresponding to the part of $\varphi$ implemented by $S_1$ corresponds to the specification

$$\square([0,1] a \geq 4 \rightarrow ((b \leq 0 \land c \geq 4) \lor (b > 0 \land d \geq 6)), $$

which effectively refines $\varphi$.

Next, we apply adaptive testing to $S_2$. We keep the same parameters, except that we replace location with with transition coverage. Adaptive testing procedure conducted 133 simulations in 18s. Figure 5 shows the specification coverage for $S_2$ and $\varphi$. 

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**Fig. 4.** Adaptive testing - specification coverage for $S_1$ and $\varphi$.

**Fig. 5.** Adaptive testing - specification coverage for $S_2$ and $\varphi$. 

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The main observation about this experiment is that we are able to reach the error location $s_4$ via both transitions $t_9$ and $t_{10}$ (bold arrow lines). It means that we can show two qualitatively different ways to violate the specification. Transition $t_9$ represents the violation of the obligation (sub-formula) $(b \leq 0 \land \Diamond_{[0,1]} c \geq 4)$, while $t_{10}$ indicates the violation of the obligation $(b > 0 \land \Diamond_{[0,1]} d \geq 6)$ in $\varphi$. This is in contrast to the falsification testing approach, which stops as soon as the first violation of the specification is detected.

The comparison between adaptive testing outcomes for $S_1$ and $S_2$ reveals another interesting observation – it is easier to achieve full location/transition coverage for $S_2$ than the 60%-location and 36%-transition coverage for $S_1$. In fact, the major part of testing effort goes in trying to enable transitions that cannot be enabled by any combination of admissible input/output pairs. Finally, we would like to emphasize that adaptive testing is based on a heuristic – the procedure can give some confidence to the engineer that a location is not reachable or that a transition cannot be enabled, but this indication does not represent a formal proof.

5.2 Case Study

In this section we introduce a case study that we shall use as an example to illustrate our approach. We consider the Aircraft Elevator Control System [18] to illustrate model-based development of a Fault Detection, Isolation and Recovery (FDIR) application for a redundant actuator control system.

![Diagram of Aircraft Elevator Control System](Fig. 6. Aircraft Elevator Control System [18].)
The architecture of an Aircraft Elevator Control System with redundancy is illustrated in figure 6. It has an elevator on the left and right side of the aircraft. Each elevator is equipped with two hydraulic actuators. Either actuator can position the elevator, however at any point in time at most one shall be active. Three different hydraulic systems drive the four actuators. The left (LIO) and right (RIO) outer actuators are controlled by a Primary Flight Control Unit (PFCU1) with a sophisticated input/output control law. If a failure occurs in the outer actuators or hydraulic systems, a less sophisticated Direct-Link (PFCU2) control law with reduced functionality takes over to handle the left (LDL) and right (RDL) inner actuators. The system uses state machines to coordinate the redundancy and assure its continual fail-operational activity.

This model has one input variable, the input Pilot Command, and two output variables, the position of left and right actuators, as measured by the sensors. This is a complex model. It has 426 signals, of which 361 are internal variables that are instrumented (279 real-valued, 62 Boolean and 20 enumerated – state machine – variables). When the system behaves correctly, the intended position of the aircraft required by the pilot must be achieved within a predetermined time limit and with a certain accuracy. This can be captured with several requirements. One of them says that whenever the derivative of the Pilot Command \( \text{cmd} \) goes above a threshold \( m \) followed by a period of \( \tau \) time where the derivative is smaller than \( k << m \), the actuator position measured by the sensor must stabilize (become at most \( n \) units away from the command signal) within \( T + t \) time units. This requirement is formalized in IA-STL as the specification \( \phi = (\{\text{cmd}\}, \{\text{lep}\}, \varphi) \), where:

\[
\varphi \equiv \square (\text{cmd}' \leq k \sum_{\tau} \text{cmd}' \geq m) \rightarrow \\
\Diamond_{[0,T]} [0,\tau] (|\text{cmd} - \text{pos}| \leq n)
\]

The symbolic automaton \( \mathcal{A}_\phi \) associated to the specification \( \phi \) has 241 locations.

In this case study, we perform three experiments: (1) we compare our adaptive testing approach with falsification testing, (2) we empirically study the effect of bounding the total number of simulations on the coverage, and (3) we empirically evaluate the effect of PSO parameters on the coverage.

In the first experiment, we compare our approach to falsification testing in which we use PSO as a global optimizer. We first restrict the adaptive testing procedure to have the sink error location as the only target location. For the falsification testing approach, we derived from the specification that a violating trace must have at most 40 samples. Hence, we framed the falsification testing problem as a global optimization problem of finding 40 values that represent an input sequence inducing a run in the specification automaton, which ends in the (sinc) error location. For both approaches, we set the maximum budget to 12,000 simulations. The adaptive testing method found a violating behavior by using 32 simulations executed in 121s (69s for the initialization of the model and 52s for running all simulations). The falsification testing approach could not find a violating behavior after 12,000 simulations executed in 8,854s. This experiment suggests that the specification can greatly help in incrementally
building a violating trace – the structure of the automaton can be used to guide step-by-step the search for the right sequence of inputs.

In the second experiment, we vary the adaptive testing budget, i.e. the maximum number of simulations that we allow to be used. We evaluate our approach with 100, 500, 1000 and 5000 simulations. In addition, we run the adaptive testing procedure without an upper bound on the budget. The aim of this experiment is to study the effect of the budget on coverage.

Figure 7 summarizes the results of the second experiment. Without setting the budget, the adaptive testing procedure runs a total of 12986 simulations and visits 110 out of 241 locations for the 46% location coverage. We can also observe that many of the locations are already discovered and visited with a small number of simulations. The figure also shows the rate of visiting new locations per minute. We can observe that this rate is rapidly dropping with the number of simulations. It is consistent with the testing folk theory stating that it is easy to achieve most of the coverage, but that it is difficult to discover specific regions. We note that the rate can be used to define a stopping criterion for adaptive testing, which represents the desired trade-off between the exhaustiveness of testing and the testing effort.

In the third experiment, we fixed the total budget to 1,000 simulations and we varied the two main PSO parameters – the swarm size and the maximum number of iterations. We varied these two parameters by setting their values to 50, 100 and 500, respectively, for a total of 9 experiments. For each experiment, we measured the total execution time of the approach and the number of visited locations.

Fig. 7. Impact of maximum budget on coverage.
Figure 8 shows the results of the experiment. We can observe that the two PSO parameters have a negligible impact on coverage. We find this observation quite surprising. Given that PSO is a heuristic, we expected that the parameterization of the algorithm will have a greater effect on the search and hence on the number of visited locations. It turns out that the number of visited states is between 38 and 50, regardless of the choice of the swarm size and the maximum number of iterations, and the experiments do not indicate monotonicity with respect to any of the two parameters. This evaluation suggests a certain stability of the adaptive testing approach with respect to the choice of PSO parameters.

6 Conclusions and Future Work

We presented in this paper a new adaptive testing approach for covering specifications of CPS. To achieve this goal, we combine cooperative games with numerical optimization. Cooperative games use the premise that the tester and the SUT are not necessarily adversarial, and that a winning strategy may be possible under the assumption that these two entities cooperate. We use particle swarm optimization to facilitate finding actions under which the tester and the SUT can cooperate towards implementing the winning strategy. We believe that our approach provides novel methodological insights on systematic testing of CPS that at the same time aims at effectively falsifying the SUT in the presence of a fault and providing confidence in the SUT correctness in the absence of a fault.

In our opinion, the proposed approach opens many research and technological directions. Specification coverage of complex CPS requires a high number (of
potentially costly) simulations. It is not hard to see that adaptive testing admits a straight-forward parallelization in which multiple simulations can be done at the same time. We plan to implement a parallel version of our method. In this paper, the focus was on presenting the methodological aspect of our adaptive testing approach. We adopted a rather simple heuristic for exploring the specification space to avoid obfuscating the main idea with potential optimizations. We plan to explore possible improvements in the future including exploration of other numerical optimization methods, more sophisticated budgeting strategies and backtracking mechanisms. In this work, we did not address the problem of vacuous test cases that trivially satisfy the requirements. We plan to remove vacuous test cases by forbidding runs that only take Force transitions. We plan to further explore the relation between test coverage and model learning. We will finally investigate possible synergies between statistical model checking (SMC) and adaptive testing – in this case, SMC could be used to provide additional statistical guarantees about correctness of CPS.

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