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by

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SUPPORTING STRESS TESTING IN REAL-TIME SYSTEMS WITH CONSTRAINT PROGRAMMING

WARNING: Everything in this book may be all wrong. But if so, it's all right!

The Music Lesson: A Spiritual Search for Growth Through Music
VICTOR L. WOOTEN

Yet another thing I never read, but which I slap here because people will complain if this claim is not supported by a citation that looks relevant.

How far does imagination shunt inwards?
DANIEL SEAFOOTIS

Abstract

Failures in safety-critical Real-Time Embedded Systems (RTES) could result in catastrophic consequences for the system itself, its users, and the environment. Therefore, these systems are subject to strict performance requirements specifying constraints on real-time properties such as task deadlines, response time and CPU usage. Lately, RTES have been shifting towards multi-threaded application design, highly configurable operating systems, and multi-core architectures for computing platforms. The concurrent nature of their operating environment also entails that the order of external events triggering RTES tasks is often unpredictable. Such complexity in the system architecture, concurrency, and environment renders performance testing increasingly challenging. Specifically, computing input combinations that are intended to violate performance requirements, i.e., *stress testing*, is one of the preferred ways for verifying RTES performance. These input combinations are referred to as *stress test cases*, and, upon execution, are predicted to result in *worst-case scenarios* with respect to a performance requirement. In RTES, stress test cases are usually characterized by sequences of arrival times for aperiodic tasks in the subject system. Generating stress test cases is challenging because it is hard to predict how a particular sequence of arrival times will affect the system performance, and because the set of all arrival times for aperiodic tasks quickly grows as the system size increases. For this reason, search strategies based on Genetic Algorithms (GA) have been used to find stress test cases with high chances of violating performance requirements.

For practical use, software testing has to accommodate time and budget constraints. In the context of stress testing, it is essential to investigate the trade-off between the time needed to generate test cases (*efficiency*), their capability to reveal scenarios that violate performance requirements (*effectiveness*), and to cover different scenarios where these violations arise (*diversity*). Even though GA are efficient, and capable of finding diverse solutions, they explore only part of the search space, and their effectiveness depends on configuration parameters. This aspect justifies considering alternative strategies, such as Constraint Programming (CP), that explore the search space completely. Furthermore, to enable effective industrial application, stress testing has to be capable of seamless integration in the development cycle of companies. Therefore, it is both important to capture specific system and contextual properties in a conceptual model, and to map such conceptual model in a standard Model Driven Engineering (MDE) language such as UML/MARTE.

In this thesis, we address the challenges above by presenting a practical approach, based on CP, to support performance stress testing in RTES. Specifically, we make the following contributions: (1) a conceptual model, mapped to UML/MARTE, which captures the abstractions required to generate stress test cases, (2) a constraint optimization model to generate such test cases, and (3) a combined GA+CP stress testing strategy that achieves a practical trade-off between efficiency, effectiveness and diversity. The validation of our work shows that (1) the conceptual model can be applied with a reasonable overhead in an industrial settings, (2) CP is able to effectively identify worst-case scenarios with respect to task deadlines, response time, and CPU usage, and (3) the combined GA+CP strategy is more likely than GA and CP in isolation to scale to large and complex systems. The work in this thesis opens up the exploration of further directions, involving the use of multi-objective optimization to generate stress test cases that simultaneously exercise different performance properties of the system, and of MiniMax analysis to derive design and configuration guidelines that minimize the risk to violate performance requirements at runtime.

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Acronyms

API Application Programming Interface.
ASIC Application-Specific Integrated Circuit.

CCS Cruise Control System.
CIM Computation Independent Model.
CO Constrained Optimization.
COP Constraint Optimization Problem.
CP Constraint Programming.
CPU Central Processing Unit.
CSP Constraint Satisfaction Problem.

DM Deadline Monotonic.
DSL Domain Specific Language.
DSM Domain Specific Modeling.

EDF Earliest Deadline First.
EVT Extreme Value Theory.

FMS Fire and Gas Monitoring system.
FSM Finite State Machine.

GA Genetic Algorithms.
GAP Generic Avionics Platform.
GCM Generic Component Modeling.
GPL General Purpose Language.
GQAM Generic Quantitative Analysis Modeling.
GRM Generic Resource Modeling.

HDD Hard Disk Drive.
HiL Hardware-in-the-Loop.
HLAM High-Level Application Modeling.
HMBA Hybrid Measurement-based WCET Analysis.
HPSS Herschel-Planck Satellite System.
HRM Hardware Resource Modeling.

HWMT	High Water-Mark Time.
ICS	Ignition Control System.
IDE	Integrated Development Environment.
IP	Integer Program.
IUT	Implementation Under Test.
KM	Kongsberg Maritime.
LDS	Limited Discrepancy Search.
MBA	Measurement-based WCET Analysis.
MBT	Model-based Testing.
MC	Model Checking.
MDA	Model-driven Architecture.
MDE	Model-driven Engineering.
MiL	Model-in-the-Loop.
MOF	Meta-Object Facility.
NFP	Non-Functional Properties.
OCL	Object Constraint Language.
OMG	Object Management Group.
OPL	Optimization Programming Language.
PA	Parametric WCET Analysis.
PAM	Performance Analysis Modeling.
PDM	Platform Description Model.
PiL	Processor-in-the-Loop.
PIM	Platform Independent Model.
PLD	Programmable Logic Device.
PSM	Platform Specific Model.
QoS	Quality of Service.
RAM	Rapid Access Memory.
RM	Rate Monotonic.
RQ	Research Question.
RR	Round Robin.
RSM	Repetitive Structure Modeling.
RTA	Response Time Analysis.
RTES	Real-Time Embedded Systems.
RTOS	Real-Time Operating System.
SA	Static WCET Analysis.
SAM	Schedulability Analysis Modeling.

SBSE	Search-Based Software Engineering.
SBST	Search-Based Software Testing.
SiL	Software-in-the-Loop.
SRM	Software Resource Modeling.
STA	Statistical WCET Analysis.
SUT	System Under Test.
UAV	Unmanned Air Vehicle.
UBA	Utilization-Based Analysis.
UML	Unified Modeling Language.
UML/MARTE (MARTE)	UML Profile for Modeling and Analysis of Real-Time Embedded systems.
UML/SPT (SPT)	UML Profile for Schedulability, Performance and Time.
UTP	UML Testing Profile.
VSL	Value Specification Language.
WCET	Worst-Case Execution Time.
xtUML (xUML)	Executable UML.

Chapter 1

Introduction

Software in domains such as automotive, maritime, and aerospace is increasingly relying on safety-critical systems, whose failure could result in catastrophic consequences for the system itself, its users, and its environment. For this reason, the safety-related components of these systems are usually subject to third-party certification to assess its operational safety. Among several different aspects, software safety certification has to take into account performance requirements specifying how the system should react to its environment, and how it should execute on its hardware platform. Such requirements often specify constraints on real-time properties such as response time, jitter, task deadlines, and computational resources utilization [Henzinger and Sifakis, 2006]. Specifically, widely used safety standards like IEC 61508 and IEC 26262 clearly highlight the importance of performance analysis and testing, stating it is *highly recommended* for the highest Safety Integrity Levels [Brown, 2000]. However, safety-critical applications are progressively being built as Real-Time Embedded Systems (RTES), whose overall goal is monitoring, responding to, and controlling the external environment [Shaw, 2000].

As a consequence of advances in software technology, RTES have been shifting towards multi-threaded application design, highly configurable operating systems, and multi-core architectures for computing platforms [Kopetz, 2011]. The concurrent nature of the environment where these systems operate also entails that the order of external events triggering the system tasks is often unpredictable [Gomaa, 2006]. Such complexity in the system architecture, concurrency, and environment renders performance analysis and testing increasingly challenging. This aspect is reflected by the fact that most existing approaches in Software Engineering prioritize the system functionality, though the degradation in performance can potentially have more severe consequences than incorrect system responses [Weyuker and Vokolos, 2000]. In industrial contexts, this problem is mostly tackled by Performance Engineering practices. This field extensively relies on profiling and benchmarking tools that dynamically analyze performance properties [Jain, 1991]. These tools, however, are limited to producing a small number of system executions and require manual inspection of those executions. In general, such tools provide only a rough assessment of the system performance, and can only be part of a more comprehensive and systematic approach for performance evaluation.

1.1 Thesis Background

When it comes to assessing whether a software system fulfills its intended purpose, Software Engineering distinguishes between the activities of *validation* and *verification*. Traditionally, the two are meant to answer the questions “are you building the *right system*?" and “are you building the *system right*?" [Boehm, 1991], respectively. Indeed, validation ensures that the system meets the stakeholders’ requirements, and verification checks whether the system has been built according to its specification. While the former usually requires interaction with the stakeholders, the latter is based only on comparing the system artifacts with their specification. For this reason, research in software engineering has increasingly focused over the years in devising automated or semi-automated methodologies for software verification.

There exist two fundamental, complementary approaches to software verification: namely formal verification and testing. Formal verification techniques aim at mathematically proving the correctness of a system with respect to a set of properties derived from the requirements. Among several others, common approaches for formal verification include Theorem Proving [Dijkstra et al., 1976], Static Analysis [Nielson et al., 1999], and Model Checking [Clarke et al., 1999]. One of the main challenges faced by formal verification approaches is the so-called state (or combinatorial) explosion problem. Indeed, static approaches revolve around proving reachability properties over a graph of the possible system states, but exhaustively exploring all the graph paths is generally infeasible for large systems. Despite the introduction of Bounded Model Checking as a way to mitigate state explosion [Biere et al., 2003], there is no general solution to the problem [Clarke et al., 2012].

In contrast to verification, testing consists in investigating whether given input combinations (*test cases*) produce their expected system outputs as described in a *test oracle*. If some test case produces an unexpected output, then a *failure*, caused by a *fault* (or *defect*, or *bug*) in the implementation, was triggered in the system execution. The main challenge of testing is the so-called coverage problem: in general, observing the system outputs for all the possible inputs is infeasible for large systems. Furthermore, some failures occur only in highly exceptional cases, and are hard to reproduce. Several techniques try to overcome this limitation by automating the generation of test cases that reach high coverage. Popular approaches for testing are Mutation-Based Testing [King and Offutt, 1991] and Model-Based Testing [Dalal et al., 1999].

In safety-critical domains, carefully testing system performance as well as functional behavior is of paramount importance. It is common knowledge that, in general, test cases aimed at testing some functionality can also be used to evaluate system performance. However, such an approach might lead to overlooking crucial flaws in the system architecture or implementation, because it does not entail the generation of test cases specifically meant to stress the system performance. Therefore, computing input combinations that are intended to violate performance requirements has become one of the preferred ways for testing RTES performance [Millett et al., 2007]. This technique is commonly known as *stress testing*, where “ [. . .] a system is subjected to unrealistically harsh inputs or load with inadequate resources with the intention of breaking it" [Beizer, 2002].

In the context of safety-critical RTES, there are three main performance-related aspects that need to be thoroughly tested [Lee and Seshia, 2011], possibly by using stress testing approaches. These aspects concern hard real-time, soft real-time, and resource usage constraints, respectively. Hard real-time constraints are often expressed as *task deadlines*, implying that system tasks must always terminate before their given completion time. Such strict constraints entail that even a single deadline miss severely compromises the system operational safety. Soft real-time constraints imply looser bounds on task completion times, and are usually expressed as *response time* requirements, stating that the system should respond to external inputs within a specified time. Failure to do so entails negative consequences over the Quality of Service (QoS), undermining the system responsiveness. Finally, *resource constraints* specify that the usage of some resources, e.g., bandwidth, CPU, or memory, has always to be below a certain threshold.

Design analysis techniques have traditionally been used in RTES for early verification of performance requirements. For this purpose, specific methods for design-time performance analysis have been proposed [Gomaa, 2006]. Based on estimates for tasks execution times, these methods are mostly used to assess the tasks schedulability at design time through formulas and theorems from Real-Time Scheduling Theory [Tindell and Clark, 1994]. However, results from scheduling theory can be inaccurate, depending on their assumptions regarding the target RTES. In general, extending these theories to multi-core processors has been shown to be a challenge [David et al., 2010]. Therefore, in large and complex RTES, scheduling analysis techniques are usually complemented by stress testing.

When stress testing a system, the goal is to find input combinations that are likely to pressure the system to violate performance requirements, i.e., to miss task deadlines, to exhibit high response time, or high CPU usage. These input combinations are referred to as *stress test cases*, which, upon execution, are predicted to result in *worst-case scenarios* with respect to a performance requirement. In RTES, these test cases are usually characterized by sequences of arrival times for aperiodic tasks in the system under test.

Generating stress test cases is not trivial, because it is hard to predict how a particular sequence of arrival times will affect the system performance. Furthermore, the set of all possible arrival times for aperiodic tasks quickly grows as the system size increases, rendering exhaustive testing infeasible. For this reason, search strategies are needed to effectively find stress test cases with high chances of violating performance requirements. The discipline studying how to formalize Software Engineering problems in a way that allows them to be solved with search strategies is commonly known as Search-Based Software Engineering (SBSE), which specializes in Search-Based Software Testing (SBST) [Harman and Jones, 2001]. In SBST, the requirements to verify are usually formalized with a mathematical function that drives the search towards optimal solutions, which in turn represent test cases.

The most recent [Afzal et al., 2009] contributions that have been proposed for automated stress test cases generation are based on meta-heuristics and incomplete search, namely Genetic Algorithms (GA) [Briand et al., 2005, Briand et al., 2006, Garousi et al., 2008]. GA are search heuristics mimicking the process of natural evolution, often used to solve optimization or search problems. Although there is no universally accepted definition of GA, most of these algorithms have in common four elements: a *population* of chromosomes, selection according to *fitness*, *crossover* to produce new offspring and random *mutation* of individuals [Mitchell, 1998]. Chromosomes represent candidate solutions for a given problem, and consist of a set of genes, each representing a particular value in the solution. A typical GA starts by randomly generating a population of chromosomes, and calculating their fitness. GA then performs a series of generations where pairs of chromosomes are selected according a given criterion. Genes in the pair are crossed over to form two offspring, which are then randomly mutated. Finally, two chromosomes in the population, chosen with decreasing probability according to fitness, are replaced by the offspring. The main assumption behind GA is that good parents produce a good offspring, and, as in biological evolution, only fit individuals survive and proliferate. Indeed, during a series of generations, the fittest chromosomes tend to survive in the population, while the unfit are discarded.

For practical use, software testing has to accommodate time and budget constraints. In the context of stress testing, it is essential to investigate the trade-off between the time needed to generate test cases (*efficiency*), their capability to reveal scenarios that violate performance requirements (*effectiveness*), and to cover different scenarios where these violations arise (*diversity*). It is known that, in most applications, the incomplete and randomized nature of GA makes this class of algorithms efficient, and capable of finding solutions highly diverse from each other [Goldberg, 2006]. Nonetheless, when it comes to devising a stress testing approach suitable for use in large industrial systems, there are two main reasons that justify the investigation of alternatives to GA. First, GA is an incomplete and randomized search strategy that explores only part of the input space. This means that, depending on the choice for the initial population, GA could converge to plateaus yielding suboptimal solutions that characterize ineffective test cases, i.e., test cases that are not likely to break task deadlines, response time, or CPU usage requirements. Second, GA relies on a set of parameters that have a significant impact on the search and therefore need to be tuned. Examples of these parameters are the probabilities of crossover, mutation and replacement, the population size, and its initial chromosomes. A suboptimal choice for the value of these parameters could once again lead the search to subspaces with ineffective solutions.

Addressing the above challenges leads us to consider strategies that both explore the search space completely, and whose results do not depend on specific search parameters. Among all the techniques fulfilling these two characteristics, Constraint Programming (CP) has been able to effectively solve search problems in a variety of domains [Rossi et al., 2006], and therefore represents a good candidate for a stress testing search strategy. Specifically, CP has successfully been used to generate best- and worst-case schedules, especially in the domain of job-shop scheduling problems [Baptiste et al., 2001]. Furthermore, CP is very well supported by both free and commercial tools that also provide APIs in several programming languages for building and developing domain-specific applications [Benhamou et al., 2010]. This last point is essential to develop any automated approach that aims at being used on industrial scale. CP is a programming paradigm where relations among variables are expressed in form of constraints [Apt, 2003]. Specifically, CP can be used to solve Constraint Optimization Problems (COP), where the goal is to find a solution which maximizes a given objective function under constraints. This is usually done by branch and bound algorithms that, when combined with a complete labeling strategy over the domains of variables, compute the global optimum of a COP. Branch-and-bound algorithms usually iterate over three steps: (1 – *branch*) divide a set of candidate solutions into two or more partitions, (2 – *bound*) compute bounds for the value of the objective function in one set of candidate solutions, and (3 – *prune*) possibly discard sets of candidate solutions that are shown to be sub-optimal or infeasible. The common representation of a branch and bound algorithm is a *branching tree*, since recursively applying the branch step starting from the whole search space defines a tree structure whose nodes are the candidate solutions, and whose edges are the node branches. Branch and bound algorithms are also supported by search heuristics, i.e., problem-specific techniques used to speed up the search process, for instance by specifying the selection policy for the node to branch at each iteration. Due to its completeness, the search may take time to terminate and hence heuristics can be used to shorten the search time by providing a quicker convergence towards the global optimum. COP are represented in constraint models that include constant values, variables, constraints, and an objective function. Solutions for such models are found by constraint solvers, which implement solving algorithms that use techniques such as constraint propagation and domain filtering, and often allow to specify of user-defined search heuristics.

When devising a stress testing approach that aims at being suitable for industrial use, there are aspects to consider other than choosing the appropriate search strategy. First, even though RTES share some commonalities, they all require domain-specific configurations. This implies that, to enable effective stress testing, a conceptual model capturing specific system and contextual properties is required. Abstracting the main concepts needed for an analysis is indeed the first step in devising a generalizable approach that is not tied to a specific system [Lindland et al., 1994]. Second, to enable effective industrial use, approaches have to be capable of seamless integration in the development cycle of companies. Nowadays, Model Driven Engineering (MDE) has become popular in industry as a way to handle increasing software complexity through the systematic use of models during development [Hutchinson et al., 2011]. To simplify its application in standard MDE tools, a conceptual model has to be mapped to a standard modeling language. In the context of RTES, reasoning about performance requirements such as deadline misses, response time, and CPU usage requires the explicit modeling of time, which is one of the key characteristics of the UML Profile for Modeling and Analysis of Real-Time and Embedded Systems (UML/MARTE, in short MARTE) [OMG, 2011a]. MARTE is meant to support the specification, design, and verification/validation of RTES, focusing on performance and scheduling analysis. Therefore, it represents the reference modeling framework when mapping the abstractions needed for stress testing to a standard modeling language.

1.2 Thesis Contributions

In this thesis, we addressed the challenges above by presenting a practical approach, based on Constraint Programming (CP), to support performance stress testing in Real-Time Embedded Systems (RTES). Specifically, we make the following contributions:

1. **A conceptual model to support stress testing in Real-Time Systems.** We provide a conceptual model that captures, independently from any modeling language, the abstractions required to support stress testing of task deadlines, response time, and CPU usage in RTES. We also provide a mapping between our conceptual model and UML/MARTE, in order to simplify its application in standard MDE tools. The subset of UML/MARTE that corresponds to out conceptual model contains tagged values and stereotypes that extend UML sequence diagrams, which are popular for modeling concurrent systems such as RTES. The conceptual model has been validated in a Fire

and Gas monitoring System (FMS) for offshore platforms, concerning performance requirements for safety-critical I/O drivers. The validation shows that the conceptual model can be applied in industrial settings a practically reasonable overhead, and enables the definition of a search strategy for worst-case scenarios with respect to performance requirements. This contribution has been published in a conference paper [Nejati et al., 2012], and is discussed in Chapter 5.

2. **A CP-based search strategy to identify worst-case scenarios in RTES.** We cast the problem of generating stress test cases for task deadlines, response time, and CPU usage as a Constraint Optimization Problem (COP) over our conceptual model. The COP implements a preemptive task scheduler with fixed priorities, and, upon resolution, generates worst-case scenarios that can be used to characterize stress test cases. The COP is the result of a refinement process over four iterations in two years. (1) First, we devised a COP implemented in COMET [Hentenryck and Michel, 2009], a constraint programming language that supports both modeling and search heuristics. In that work, we addressed the verification of CPU Usage and response time requirements. This first iteration has been published in a conference paper [Nejati et al., 2012]. (2) Then, we implemented a second version of that model in the Optimization Programming Language (OPL) [Van Hentenryck, 1999], which, while retaining the same features as COMET, is also supported by a large community. In that work, we focused on generating worst-case scenarios for task deadline misses. This second iteration has been published in a workshop paper [Di Alesio et al., 2012]. (3) Subsequently, we included a dedicated search procedure for a smarter labeling of variables, in order to provide a faster convergence of the search towards optimal solutions. However, these first three versions of the model included a variable boolean matrix showing tasks execution over time, which proved to severely limit the efficiency of our model. This third iteration has been published in a conference paper [Di Alesio et al., 2013]. (4) To overcome this weakness, we finally improved the data structures representing task executions by considering a discretized matrix, as opposed to a boolean one, to represent task executions over time. This fourth iteration has been published in a conference paper [Di Alesio et al., 2014]. We validated the COP in the FMS, and in five other subject systems from several safety-critical domains. The validation on the industrial system shows that CP is effectively able to find scenarios that break task deadlines and violate response time and CPU Usage requirements. On the other hand, the validation on the other five subject systems shows that, when compared to GA, CP is more effective, but less efficient and generates stress test cases that are less diverse. This contribution is discussed in Chapter 6.
3. **A combined GA+CP search strategy to identify worst-case scenarios in RTES.** We devise a search strategy to generate stress test cases, namely GA+CP, that combines GA and CP to provide higher scalability by retaining the efficiency and solution diversity of GA, and the effectiveness of CP. The key idea behind GA+CP is to further improve the solutions computed by GA by performing a complete search with CP in their neighborhood. In this way, GA+CP takes advantage of the efficiency of GA, because solutions are initially computed with GA, and the subsequent CP search is likely to terminate in a short time since it focuses on the neighborhood of a solution, rather than on the entire search space. GA+CP also takes advantage of the diversity of the solutions found by GA, because CP performs a local search in subspaces defined by GA solutions. Similarly, GA+CP takes advantage of the effectiveness of CP since, once GA has found a solution, CP further improves it by either finding the best solution within the neighborhood, or proving upon termination

that no better solution exists. We validated GA+CP using the same five subject systems as GA and CP in isolation. The validation shows that, in comparison with GA and CP in isolation, GA+CP achieves nearly the same effectiveness as CP and the same efficiency and solution diversity as GA, thus combining the advantages of the two techniques. This contribution has been accepted for publication in a journal [Di Alesio et al., 2015], and is discussed in Chapter 7.

1.3 Thesis Outline

This thesis is organized in two Parts. Part I describes the theoretical foundations behind our work, and defines the problem of identifying worst-case scenarios with respect to performance requirements. This Part consists of two Chapters:

1. **Chapter 2 – Background** introduces the background of the thesis, ranging from Real-Time Embedded Systems (RTES) to Model-Driven Engineering (MDE), Software Testing, and Mathematical Optimization.
2. **Chapter 3 – Problem Description** casts the problem of stress testing RTES performance to the identification of worst-case scenarios. The problem is first illustrated through an example, and then specified in a safety-critical industrial system from the maritime and energy domain concerning a Fire and Gas monitoring System (FMS) for offshore platforms.

Part II describes the contributions of the thesis, comparing our work with similar approaches. This Part consists of five Chapters:

1. **Chapter 4 – An Overview of Stress Testing in Real-Time Embedded Systems** introduces our methodology for generating stress test cases in Real-Time Systems. The approach consists of modeling the system in UML/MARTE, and searching for worst-case scenarios using a combination of Genetic Algorithms (GA) and Constraint Programming (CP). These key components of our approach are described in the following three sections.
2. **Chapter 5 – UML/MARTE Modeling** describes a conceptual model defining the key abstractions to identify worst-case scenarios in RTES. The conceptual model maps to a subset of UML/MARTE, and has been validated in the FMS.
3. **Chapter 6 – Generating Stress Test Cases with CP** describes how to cast the generation of stress test cases as a Constrained Optimization Problem (COP). The Chapter details the constrained optimization model, which is validated in the FMS, and on a set of five subject systems from other safety-critical domains.
4. **Chapter 7 – Generating Stress Test Cases with GA+CP** describes how to combine CP with GA for the purpose of identifying worst-case scenarios with respect to performance requirements. The Chapter details the combined search strategy, which is validated on the same set of five subject systems used to validate the CP-based strategy.
5. **Chapter 8 – Discussion and Related Work** places our work in the four main relevant areas of the literature, namely methodologies for verifying RTES, Model-based and Software Testing approaches, and search techniques used for Mathematical Optimization.

Finally, **Chapter 9 – Conclusions and Future Work** summarizes the thesis contributions and discusses perspectives on future work.

Part I

Foundations and Context

Chapter 2

Background

Embedded Systems are cyber-physical systems built to perform a specific function, and whose software components are tightly coupled to external hardware devices (Section 2.1). Several Embedded Systems have to satisfy strict timing constraints on their computations, and are therefore referred to as Real-Time Embedded Systems (RTES). RTES are extremely common in safety-critical domains, where even a single failure can potentially result in catastrophic consequences. Therefore, RTES have to undergo a rigorous quality assessment process to ensure that their operation does not pose uncontrolled risks for the users, the system itself, and the environment. In particular, most RTES are developed as concurrent systems, where functionalities are implemented in several interdependent tasks that interact with each other. Whether these tasks are going to satisfy timing constraints at runtime is determined by their schedule, which is in general unpredictable prior to the system execution. For this reason, the early development phases of RTES are built upon scheduling (Section 2.1.1) and performance analysis techniques, in order to assess as early as possible whether the system is likely to meet its expected performance at runtime. While the former are mostly based on theorems from scheduling theory, the latter are based on design-time analysis (Section 2.1.2) and simulation (Section 2.1.3).

RTES in industrial applications can be very large, and hence are developed using methodologies aimed at managing software complexity. The most used of such methodologies is Model-Driven Engineering (MDE), which simplifies the understanding of a system through the use of modeling abstractions (Section 2.2). Indeed, the key idea behind MDE is to use of models in order to abstract the system details, and to specify such models using metamodels (Section 2.2.1). One of the most acknowledged implementations of MDE is the Model-Driven Architecture, defined in 2001 by the Object Management Group (OMG) (Section 2.2.2.1). MDA defines the Unified Modeling Language (UML) as the reference language to describe models (Section 2.2.2.2). UML is a general-purpose framework suitable to develop a variety of systems, but it is not expressive enough to represent every domain-specific abstraction. In the context of RTES, UML is extended by the profile for Modeling and Analysis of Real-Time Embedded Systems (UML/MARTE, in short MARTE) which defines abstractions specific to the RTES domain (Section 2.2.2.3). In particular, MARTE provides modeling facilities to support the definition of scheduling and performance analysis methodologies of RTES.

However, design-time analysis is often not sufficient to guarantee that the system satisfies all of its requirements during operation. This is because such analysis either makes restrictive assumptions, or requires a description of the system at a level of detail which is hard to manage for large industrial applications. For this reason, design-time techniques are often complemented with testing, which aims at trying input combinations on a system implementation, and checking whether or not these inputs produce expected outputs (Section 2.3). In particular, the principles of MDE have been applied to software testing, leading to the definition of Model-Based Testing (MBT) as an approach to derive test cases from the system specification (Section 2.3.1). In general, there exist several software testing techniques, most of which focus on the system functional aspects. However, in the context of RTES, performance testing plays a major role, because it complements design-time scheduling analysis in order to ensure that the system satisfies its real-time constraints (Section 2.3.2). Performance testing in safety-critical RTES often revolves around stress testing, intended as a way to test the system under the worst operating conditions. Specifically, stress testing in RTES aims at finding sequences of inputs and their timing that maximize the chance to break task deadlines or to violate constraints on response time and CPU usage. Finding these sequences of inputs is hard in general, because the set of possible task arrival times is too large to be exhaustively tested for large and complex systems. For this reason, stress testing is often cast as a search problem, similar to several other problems in Search-Based Software Testing (SBST) (Section 2.3.3).

Search problems consist in finding, among a large set of alternatives, a set of solutions which fulfill given criteria. These criteria are often formulated as objective functions in some variables, so that search problems consist in finding values for these variables which minimize or maximize the objective functions. Mathematical Optimization is the discipline describing methods to solve these optimization problems (Section 2.4). There exist several techniques in Mathematical Optimization, which mostly depend on the shape of the objective function, and on the types of restrictions on the values for its variables. For instance, Constrained Optimization focuses on problems where the variables of the objective function are subject to constraints, such as logical relations among boolean values, and equalities or inequalities among integer and real values (Section 2.4.1). Problems in Constrained Optimization are usually solved through the means of Constraint Programming (CP), which is a declarative paradigm where relations among variables are expressed in form of constraints. CP is largely used to solve both Constraint Optimization Problems (COP) and Constraint Satisfaction Problems (CSP), which are particular COP where the objective function is constant and the variables only appear in constraints. CSP are usually solved using a tree representation of the variables values. The tree is then visited, backtracking each time an assignment breaks a constraint (Section 2.4.1.1). Popular techniques to solve COP are also based on tree search and backtracking, with the addition of keeping track of the best solution found (Section 2.4.1.2). These tree search approaches for CP exhaustively explore the search space, and are guaranteed to return the optimal solution upon termination. CP have been used in several applications, including scheduling analysis, formal verification, and software testing. However, there exist practical problems which are hard to formulate as COP, and even when modeled through constraints they can not be solved to optimality in convenient time. For this reason, SBST often solves problems using randomized algorithms, which start by generating solutions at random, and then manipulate them to achieve better values of the objective function. These algorithms are collectively known under the name of Metaheuristics, and, in contrast to methods in CP, do not exhaustively explore the search space (Section 2.4.2). Random Search and Hill-Climbing are the two most basic implementations of metaheuristics (Section 2.4.2.1). Random Search randomly generates solutions from scratch, thus exploring the search space. On the other hand, Hill-Climbing randomly generates a solution, and then improves it by making random modifications, thus exploiting the initial solution. Exploration and exploitation are the two dimensions determining the trade-off between gaining confidence that the search gets close to the global optimum, and finding a solution with a satisfactory objective value. In general, all metaheuristics achieve such trade-off by combining Random Search and Hill-Climbing. Genetic Algorithms (GA) have been successfully used in SBST due to their flexibility in combining explorative and exploitative behavior (Section 2.4.2.2). GA start from an initial set of randomly generated solutions, and then combine them through crossover and mutation operators, mimicking the natural evolution process of individuals. In the context of SBST, GA have been extensively used for test case generation, and in particular to generate stress test cases for RTES.

2.1 Real-Time Embedded Systems (RTES)

An Embedded System is a computing system where software and hardware are tightly coupled in order to perform a specific function. In contrast to general-purpose systems such as personal computers, these systems are integrated (*embedded*) as part of a larger system and often use specific computational and external hardware. Embedded systems are the backbone of a variety of domains, ranging from microwave ovens and washing machines, to satellite and nuclear power plant control systems [Barr and Massa, 2006]. Many embedded systems operate in *safety-critical* domains, where failures can result in severe damage of the system itself, harming its users and the environment [Knight, 2002]. For instance, a malfunction in an air traffic monitoring system can lead to an airplane collision with catastrophic consequences. Most of the time, in safety-critical domains the correct behavior of embedded systems does not only depend on the result of the computation, but also on the time when the result has been computed. For instance, the Anti-lock Braking System (ABS) of a vehicle has to activate within milliseconds after the driver breaks, as failure to do so may result in a vehicle skid due to the wheels locking up. In general, embedded systems that have to satisfy these *real-time constraints* for computing the results are defined as Real-Time Embedded Systems (RTES) [Burns and Wellings, 2001].

RTES usually interact with the external environment through *sensors* and *actuators*, as in Figure 2.1. Sensors detect the status of the environment, and communicate it to the embedded software components executed by the hardware computing platform. Based on this input, the system decides to activate one or more actuators, whose operation changes the status of the environment. A typical example is a fire monitoring system: when smoke and temperature sensors detect a fire, the system activates the water sprinkles. In this way, the sprinkles extinguish the fire, so that the sensors do not detect anymore anomalies in smoke and temperature levels. Therefore, the system finally deactivates the sprinkles. This behavior fundamentally implements a feedback control loop, similar to Proportional-Integral-Derivative (PID) controllers from control theory [Lee and Markus, 1967]. Indeed, many devices that implement control loops, such as digital controllers, signal processors, or sampled-data systems, are implemented as RTES [Liu et al., 2000].

Similar to most software systems, RTES are designed in a layered architecture consisting of three

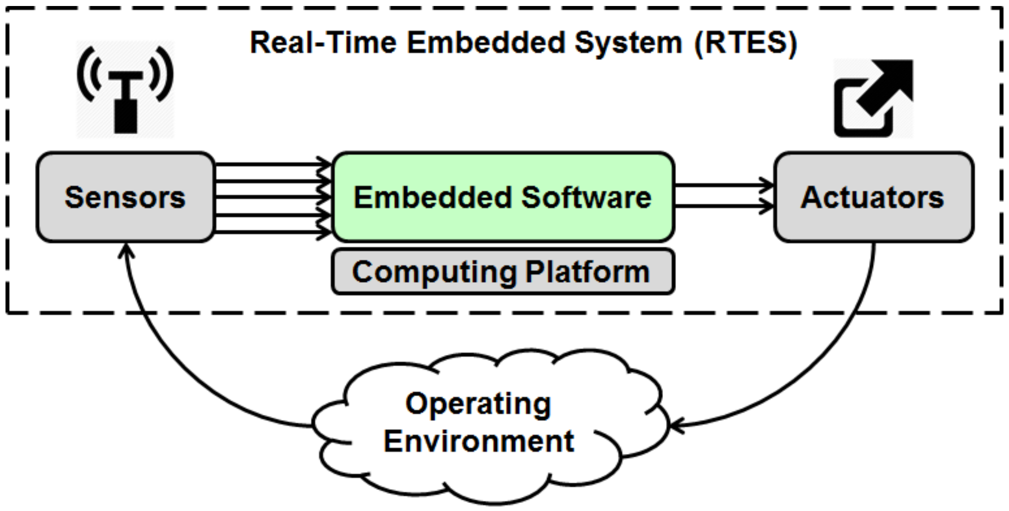
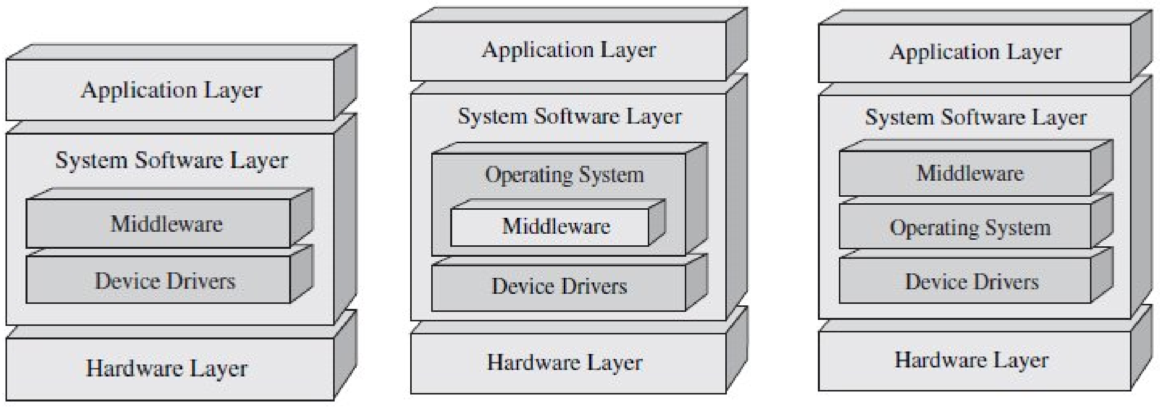


Figure 2.1. Typical operating scenario of Embedded Systems, where external sensors examine the environment state. Based on this input, the system activates some specific actuator, changing the state of the environment

main tiers, as in figure Figure 2.2 [Noergaard, 2005].



(2.2.1) RTES without Operating System (2.2.2) RTES with Operating System and integrated middleware (2.2.3) RTES with Operating System and higher-level middleware

Figure 2.2. Typical RTES architectures [Noergaard, 2005]

- **Hardware Layer.** This layer contains the physical components of the system, including external hardware, such as sensors and actuators, and computing hardware, such as memory, processor, and network. The system and application software layers contain instead the software components of the system.
- **System Software Layer.** This layer contains *device drivers*, which provide interfaces to hardware devices. Drivers implement basic functionality such as I/O and power management, allowing upper software layers of RTES to access hardware functions independently from hardware details. Furthermore, the system software layer also contains the *middleware*, which is an abstraction layer

that provides interoperability and connectivity mechanisms in systems with several applications. In simple systems (Figure 2.2.1), the middleware is a thin layer mediating between device drivers, and high-level applications. In larger systems, the functionalities of the middleware can be implemented within a *Real-Time Operating System (RTOS)*, as in Figure 2.2.2. A RTOS is a set of software libraries managing hardware and software resources to provide common services for applications. Other than providing middleware functionalities, RTOS also implement management functions for concurrent processes. Large RTES often have a distributed architecture, and consist of several sub-systems where different system software layers communicate. In those (Figure 2.2.3), the middleware is usually defined as the layer allowing interoperability between different RTOS.

- **Application Layer.** This layer implements the system logic, defining the type and scope of the RTES. Software in the application layer decides what actions a RTES takes upon receiving input from the sensors.

RTES are usually classified depending on how strict their real-time constraints are. These constraints often specify requirements on two important activities in real-time process management, namely *resource allocation* and *dispatching*. Resource allocation determines *how much* of the computational resources are allocated to the system processes, while dispatching determines *how often* such resources are allocated to the processes. Specifically, the literature defines *hard-*, *soft real-time* and *best effort systems* [Brandt et al., 2003]. Figure 2.3 classifies real-time systems based on the relative tightness of resource allocation and dispatching requirements, ranging in the graph axes from loose to tight.

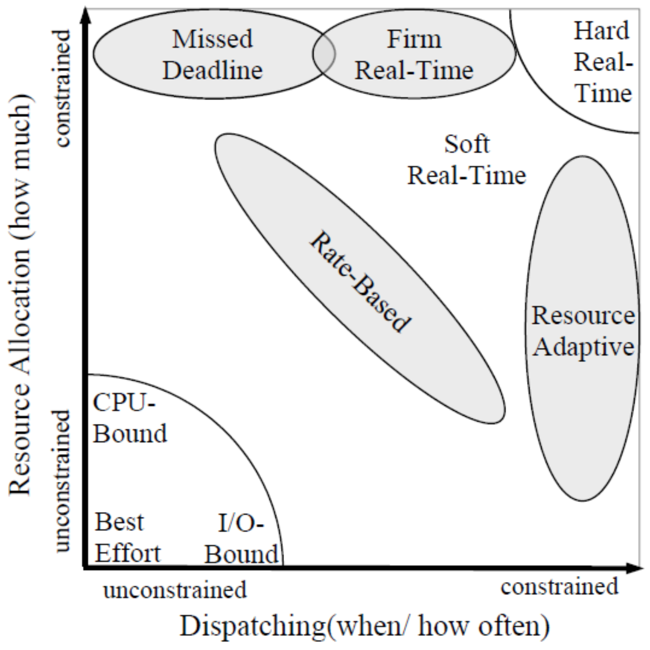


Figure 2.3. Classification of Real-Time Embedded Systems based on resource allocation and dispatching requirements [Lin et al., 2006]

- **Hard Real-Time Systems** have to respond to external inputs within strict time bounds. Failure to do so can have potential catastrophic consequences: indeed, most safety-critical systems are hard real-time systems. Systems in the transport, maritime, energy, and military domains often fall in this class. The timing requirements in these systems are often expressed in terms of *deadlines*, i.e., latest completion times for operations. Missing even a single deadline in a hard real-time system invalidates the computation results, compromising system safety. For this reason, hard real-time systems often have no fault tolerance with respect to missed deadlines.

- **Soft Real-Time Systems** do not have the same strict timing requirements as hard real-time systems, as their output is valid to some extent even in cases where deadlines are missed. For this reason, real-time constraints in soft-real time systems are often expressed in terms of *response time* rather than deadlines. Media streaming systems are common examples of soft real-time systems: if the incoming stream can not be decoded in time and a single frame is lost, end-users are not likely to notice the missing frame. However, if several frames in a row are lost, the system *Quality of Service (QoS)* suffers a negative impact. For this reason, soft real-time systems often present some degree of fault tolerance with respect to unsatisfied real-time constraints. Soft real-time systems are usually divided into four sub-categories, depending upon the extent to which resource allocation and dispatching constraints are relaxed.
  - **Missed Deadline Soft Real-Time Systems** can miss any number of deadline misses in case no computational resource are available [Jones et al., 1997]. This is often the case for systems that are not capable of adapting their QoS to the available resources, and for which a timely computation of the results is not critical.
  - **Firm Real-Time Systems** have more strict dispatching requirements than Missed Deadline systems, because in their operational context late results have little or no value [Bernat et al., 2001]. Usually, these systems can miss only some of their deadlines before their behavior is deemed unsatisfactory. In particular, *statistical* firm real-time systems allow a given percentage of processes to miss their deadlines, limiting the number of consecutive deadline misses. On the other hand, *pattern-based* firm real-time tasks allow deadline misses under user- or system-defined patterns, for instance requiring at least m out of every k jobs to meet their deadlines.
  - **Resource Adaptive Real-Time Systems** are designed to adapt their resource usage, and hence their QoS, based on the available resources [Burns, 1991]. These systems can either adapt via *discrete* or *continuous QoS levels*. For example, in adaptive control systems control task are allowed to use different sampling periods chosen from a discrete set. On the other hand, a chess engine designed to play timed games continuously adapts its performance based on the available time. The system always outputs a legal move before the time is over, even though the more time it spends, the better the chosen move is. Note that, when resources are insufficient, missed deadline systems miss their deadlines, while resource adaptive systems adapt their performance to the available resources.
  - **Rate-Based Real-Time Systems** are the most flexible in terms of resource allocation and dispatching constraints, even though they require an average resource rate for correct operation [Jeffay and Bennett, 1995]. Specifically, if a large amount resources is provided, then a long time may elapse before the next allocation. On the other hand, if less resources are allocated, then the subsequent allocation has to happen within short time. In general, the

flexibility of rate-based systems is achieved by temporarily storing the output data in buffers until resources are available.

- **Best-Effort Systems** can run without a considerable amount of resources, and are subject to flexible dispatching requirements. Within this class, non-interactive CPU-bound systems generally need a significant amount of CPU, but they usually perform low-priority operations whose execution is not urgent. On the other hand, I/O-bound processes are often interactive, and even though they use relatively little CPU, they need a faster dispatching in order to provide a satisfactory responsiveness. In general, best-effort systems are not subject to strict real-time constraints, and hence fall outside the scope of this thesis.

RTES can also be orthogonally characterized by the way system tasks are activated, i.e., by the tasks *activation type*. This distinction is the basis for the following definitions of *time-triggered* and *event-triggered real-time systems* [Kopetz, 1991].

- **Time-triggered Systems** are controlled by the progress of time, as their tasks are activated at regular intervals of time called *periods*. For instance, wind shear detection systems are time-triggered: at regular interval of times, the system polls the external sensors to detect spikes in the wind speed and direction.
- **Event-triggered Systems** are instead controlled by the arrival of events. These systems are characterized by aperiodic execution, since the triggering events are often unpredictable. For instance, the cruise control system of a vehicle is event-triggered: whenever the driver accelerates or breaks, the system adjusts the cruising speed.

RTES are often defined either as hard real-time, or as soft-real time, depending on how critical is a timely response for the system. However, large and complex systems can be both time-triggered and event-triggered. This usually happens in systems where periodic behavior coexists with signals coming from the environment. For instance, a flight control system periodically monitors air pressure and temperature, but also activates wing flaps or air brakes when the pilot interacts with the flight controls [Pinedo, 2012].

2.1.1 Scheduling in RTES

RTES are often developed as *concurrent systems*, where several computations are executed in parallel by the Real-Time Operating System. The basic abstraction for such computations is a *process*, i.e., a program in execution managed by the system [Tanenbaum, 2009]. A Real-Time Operating System assigns a set of resources to a process, such as CPU time to perform computations, and disk access to perform I/O operations, and address space in memory. Therefore, that there exist some overhead in managing a process, as each process is given its own resources. If multiple resources of the same kind are available, such as CPU cores in a multi-core hardware platform, the system can exploit *hardware parallelism* to efficiently run computations. However, if this is not the case, such as in single-core platforms, the RTOS can constantly alternate the processes giving each process access to the resource for a short time. This behavior, called *pseudo-parallelism*, is mostly used by legacy systems to emulate concurrent behavior in single-core environments. Besides processes, operating systems also allow the definition of *threads*, i.e., light-weight processes whose creation and execution demands less overhead for the RTOS. Indeed, threads belong to a *parent process*, so that each thread shares their parent resources. When reasoning about performance in the context of RTES, the differentiation between processes and threads is often not necessary. This is because the time overhead in managing processes or threads is negligible compared to real-time constraints on the tasks duration, and on the time when tasks are activated. For this reason, in this thesis we use the generic term *task* to indicate both processes and threads.

Following from the classification of RTES based on the activation type, the literature defines four main types of tasks [Sprunt et al., 1989].

- **Periodic tasks** are activated at regular interval of times, since they have a specific occurrence frequency. Tasks in time-triggered systems are periodic.
- **Aperiodic tasks** can be activated at any time instant by a triggering event. In general, we say that an aperiodic task *arrives* when its triggering event activates it[1]. Tasks in event-triggered systems are aperiodic. Specifically, *Unbounded* aperiodic tasks are triggered by a number of events for which it is not possible to establish an upper bound. On the other hand, *Bursty* aperiodic tasks are triggered by a bounded number of events. In general, events triggering aperiodic tasks may arrive with an arbitrarily short distance between them. In some cases, it is possible to determine the minimum and maximum intervals of time that separates two consecutive executions of aperiodic tasks. In this case, the task is said to be *sporadic*. When analyzing the execution of tasks, the minimum and maximum intervals of time separating two executions can be assumed equal to the smallest and the largest intervals of time considered by the analysis, respectively. For this reason, in this thesis we use the term *aperiodic* to also describe sporadic tasks.
- **Singular tasks** are executed only once. In general, they are either periodic tasks whose period is equal to the total execution time of the system, or aperiodic tasks whose triggering event is known to be fired only once. Tasks implementing an infinite loop are usually also singular.

The temporal requirements and constraints that regulate tasks execution are usually represented as task *attributes*, which we describe hereby [Sprunt et al., 1989].

- **Period.** The period specifies how often a periodic task is activated. The task period is inversely proportional to its frequency in time.
- **Minimum and Maximum Interarrival Time.** The minimum and maximum interarrival times specify the smallest and the largest intervals of time separating two consecutive executions of aperiodic tasks.
- **Arrival Time.** The arrival time is the moment when a task is activated. Note that this definition implies that the arrival time of periodic tasks is known prior to the execution of the system, as it is function of its period. On the other hand, the arrival time of aperiodic tasks is only known at runtime when the corresponding triggering events occur.

[1] In the literature, the most common nomenclature is that periodic tasks are *activated* (at regular intervals of time), while aperiodic tasks *arrive* (when some event triggers them). To avoid confusion, in this thesis we do not distinguish between the two terms, since usually periodic tasks are activated by events sent by RTOS, and the arrival of aperiodic tasks corresponds to their activation.

- **Offset.** The offset specifies the time, counted from when the system starts, when the first occurrence of a periodic task arrives. Usually, the period of the most important periodic tasks start as soon as the system is executed, and hence their offset is zero. However, there exist some periodic tasks which are designed to wait some time before their period starts, usually to allow the RTOS to allocate resources necessary for their execution.
- **Release.** The release specifies the time, counted from its arrival time, when a task can start being executed. In general, critical tasks are executed as soon as they are activated. However, there exist some tasks which are designed to wait some time after their arrival before starting. Similar to the case of tasks with non-zero offsets, this is to allow resource allocation from the RTOS. Furthermore, we also say that a task is *ready for execution* upon its arrival time, plus its release time. Note that, in the literature, arrival times are sometimes called *release times*. However, the definitions we gave imply that the arrival time of a task is equal to its release time only if its release is zero.
- **Delay.** The delay specifies the time that has to occur between the execution of two occurrences of the same task. In general, when a task finishes its execution, its next occurrence is executed as soon as it is ready for execution, and there are available computing resources. However, in some cases, a task might be designed to wait some time after the completion of its preceding occurrence, usually to avoid monopolizing the RTOS resources.
- **Duration.** For scheduling purposes, the duration represents the longest time a task takes to execute its code when there is no interruption. This is often referred to as Worst-Case Execution Time (WCET). In general, the WCET for a task is unknown since it depends on a series of context factors including software libraries, programming languages, external and computational hardware. However, there exist several techniques to estimate the WCET (Section 2.1.2).
- **Deadline.** The deadline specifies a constraint on the completion time of a task, and is expressed relative to the time when a task has been activated. In general, every task has to complete before its deadline, as failure to do so poses a severe threat on the system safety.
- **Priority.** The priority is a value that represents the relative importance between tasks in the system. Higher priority tasks have execution precedence over lower-priority ones, which might get interrupted (*preempted*) if there are not enough computational resources available for concurrent execution.

In large RTES, tasks also *interact* with each other to implement complex functionalities, which require advanced features such as synchronization and communication. For example, tasks can also share computational resources with exclusive access. This is common in case of locks upon *critical sections*, whose access is usually synchronized by semaphores. Note that tasks sharing the computational resource can not run in parallel. In this case, we say that the tasks *depend* on each other. Another common type of task interaction happens if a task, during its execution, can trigger other tasks. This is common in cases when, due to particular conditions, the triggering task has to perform additional operations which take place in the triggered tasks [Andrews, 1991]. In this case, we say that the triggering task *triggers* the triggered task[2].

[2] Note that, when discussing tasks in generic contexts, we say that tasks are *interdependent* to mean that they interact with each other through dependencies, triggering, or both.

In general, a task j consists of an ordered list $[a_1, a_2, \ldots a_n]$ of operations a_i executed in sequential order. We refer to these operations as task *activities*. At the lowest level of abstraction, an activity is a single statement in the source code of a task. For this reason, arrival times, durations, releases, and delays, can also be considered at activity-level. For example, the duration of an activity is its WCET. Similarly, the delay time of an activity a_i is the time expected to elapse between the completion of a_i, and the start of a_{i+1}. Since activities are executed in sequential order, this means that the arrival time of an activity a_i is the time when the preceding activity a_{i-1} finishes executing, plus the delay of a_{i-1}. Finally, the release of an activity a is the time, counted from its arrival time, that a has to wait before being able to execute. Note that release and delay times between activities usually correspond to *sleep* calls in the task source code. Task interactions can be considered at activity-level as well. In this case, an activity within a task can depend on an another activity in a different task, can trigger an activity in a different task, or can trigger another task. For example, an activity can trigger another activity of a waiting task by sending a specific message to that task, or can trigger a new task by launching it. Note that, for scheduling purposes, a task $j = [a_1, a_2, \ldots a_n]$ with priority p consisting of n activities a_i can be considered as a sequence $[j_1, j_2, \ldots j_n]$ of n tasks with priority p, where the duration of j_i is equal to the duration of a_i, and where j_i triggers j_{i+1}. In this case, each task j_i inherits the dependencies and triggering relationships of the corresponding activity a_i. Also note that this property holds under the assumption that the RTOS overhead for managing tasks in negligible compared to their execution and interarrival times. However, this assumption is realistic in most RTES, as discussed in the beginning of this section. Given the property above, when not specified otherwise, in this thesis we only consider tasks and task-level interactions.

The collection of tasks that constitute a system is called the system *task set*, and we refer to the set of all task arrival times in a task set as *arrival pattern*. When a task set is executed, the operating system assigns tasks to the free CPU cores. If there are more tasks available for execution than CPU cores, the RTOS decides when and which task to schedule for execution. This operation is called *scheduling*, and produces a *schedule*, i.e., an order in which tasks are executed, and possibly preempted[3]. RTOS implement different *scheduling algorithms* to schedule concurrent tasks according to different *scheduling policies* that specify the logic behind task scheduling. The main purposes of a scheduling algorithm is to minimize resource starvation, and to ensure fairness amongst the executing tasks.

There exists a variety of scheduling algorithms for RTOS, each serving different purposes depending on the type and goals of the RTES. A common way to classify scheduling algorithms is based on when the decisions to schedule tasks for execution are taken. *Off-line scheduling* algorithms implement static policies according to a predefined schedule. This schedule is usually generated starting from the task set *hyper-period*, i.e., the least common multiple among periods of tasks. At runtime, the RTOS dispatches tasks according to the schedule, periodically repeating the hyper-period schedule. Off-line algorithms require the task properties to be known at design time, and for this reason are mostly suitable for periodic task sets. These algorithms require very low runtime overhead, but have little flexibility with respect to aperiodic tasks, whose schedule can not be predetermined prior to execution. An example of

[3] Note that, for scheduling purposes, a task is an abstraction for a piece of code which is executed sequentially. For this reason, in this thesis we do not consider concurrency *within* tasks, but rather only concurrency *among* tasks.

off-line scheduling policy is the Round-Robin (RR), where tasks are cyclically executed according to predefined time slots. *On-line scheduling* algorithms instead dynamically perform scheduling decisions at runtime [Buttazzo, 2011]. In particular, task attributes, such as deadlines, periods, and priorities, are used by the RTOS scheduler to decide what task to execute at each time. In on-line algorithms, tasks are usually preempted if there are higher priority tasks ready for execution, but not enough computational resources to run them. For this reason, most on-line algorithms are defined as *preemptive scheduling* algorithms. One of the most common classifications of on-line algorithms is based on whether task priorities are fixed (*Fixed Priority Scheduling*) or they can be modified at runtime (*Dynamic Priority Scheduling*). For instance, in the Deadline Monotonic (DM) and Rate Monotonic (RM) algorithms, priorities are inversely proportional to task deadlines and periods, respectively [Liu and Layland, 1973]. However, task priorities can also be assigned dynamically and change at runtime. The Earliest Deadline First (EDF) is an example of Dynamic Priority Scheduling algorithm, which periodically assigns the highest priority to the task with the closest deadline [Dertouzos and Mok, 1989]. On-line schedulers can implement advanced features, such as resource reclaiming in case that a task finishes before its estimated WCET. The reclaimed resources can then be used for executing other tasks, or to lower the CPU speed in order to save power [Bernat et al., 2004]. On-line scheduling algorithms are flexible enough to handle aperiodic tasks, but a cost of a larger overhead for determining the tasks schedule.

Similar to the majority of commercial software systems, RTES have to undergo a rigorous quality assessment process before being deployed. This is especially true for safety-critical systems, where incorrect runtime behavior can not be tolerated. The quality assessment in RTES is mostly performed through the activities of *static analysis* (Section 2.1.2), *simulation* (Section 2.1.3), and *testing*[4].

2.1.2 Static Analysis in RTES

Static analysis techniques reason over abstractions of the system, and do not require its implementation. For this reason, they can be applied even at design-time, provided that the system details are known. There exist five main types of static analyses in RTES, mostly based on Scheduling Theory [Coffman and Bruno, 1976]. In scheduling theory, a schedule is defined as *feasible* iff every task in it meets its deadline. Furthermore, a task set is defined as *schedulable* iff there exists a feasible schedule for some arrival pattern. Based on these definitions, Scheduling Theory aims at determining whether or not a task set is schedulable. This is mostly done through *scheduling analysis* techniques, which use *proofs by construction* or mathematical methods called *schedulability tests*. Indeed, for off-line scheduling, a task set can be deemed schedulable upon a proof by construction, i.e., by constructing a feasible schedule. On the other hand, schedulability tests are sets of *necessary* or *sufficient* conditions for a task set to be schedulable. Whenever such conditions are both necessary and sufficient, the schedulability test is said to be *exact*. There exist schedulability tests for most scheduling algorithms used in practice [Buttazzo, 2011]: the most common are the Utilization-based Analysis (UBA) [Liu and Layland, 1973] and the Response Time Analysis (RTA) [Joseph and Pandya, 1986]. The UBA provides a sufficient, non-necessary condition for the schedulability of a task set, based on the definition of a task *critical instant* as the task

[4] Testing of RTES is discussed in Section 2.3, where we introduce software testing. Indeed, most of the principles and strategies for testing software systems also hold in the domain of RTES.

arrival time that leads to its latest completion time. A critical instant for any task occurs whenever a task arrives simultaneously with every other higher priority task. In this way, the case when all tasks arrive simultaneously represent the worst-case scenario, as more critical instants occur at the same time. The RTA provides an exact condition for the schedulability of a set of tasks based on a recursive formula calculating the time when each task end. Once these times are known, they can be compared to task deadlines to determine the schedulability of the task set.

Scheduling analysis methods are based upon a static description of the system, including the tasks Worst-Case Execution Times. However, the problem of obtaining upper bounds for execution times of programs is undecidable, as it can be reduced to the halting problem. WCET closely depend on the worst-case input for tasks, which are often unknown and hard to predict. Therefore, tasks WCET have to be estimated, as providing their actual value is practically infeasible. Nonetheless, the validity of scheduling analysis results depend on the how accurate the estimates of tasks Worst Case Execution Times are. Indeed, if these estimates are too pessimistic, a task can be predicted to miss a deadline in a scenario that will not happen at runtime because the task will not take as long as expected to execute. Similarly, if WCET estimates are too optimistic, a task that is predicted not to miss a deadline will do so at runtime because it will take longer than expected to execute. For this reason, providing reliable estimates for tasks WCET is a fundamental step to enable effective RTES analysis. This activity is commonly known under the name of Worst-Case-Execution Time Analysis (WCET Analysis), whose main approaches are described hereby [Wilhelm et al., 2008].

- **Static WCET Analysis (SA).** This approach estimates WCET by statically analyzing the task source code, together with hardware models specifying the functional and temporal behavior of the computing platform. SA is based on techniques such as *flow analysis* to compute loop bounds, and *low-level analysis* to predict cache hits or misses in memory. Since these techniques are often conservative, SA usually makes pessimistic assumptions overestimating WCET [Heckmann et al., 2003]. A particular type of SA is the Parametric (or symbolic) WCET Analysis (PA). This approach uses SA techniques to estimate WCET as functions of task parameters, rather than numerical time values. PA is usually used for on-line scheduling of tasks where the value of parameters are unknown prior to the system executions, or to find the source code blocks that have high impact on WCET. However, PA is often more complex than classical SA and thus is not effective on large and complex systems [Lisper, 2003].
- **Measurement-Based WCET Analysis (MBA).** This approach is based on end-to-end measurements performed by running the task on the hardware platform with given input combinations. Traditionally, execution times are measured by adding instrumentation to the task source code that generates a trace of time stamps. However, this instrumentation code requires time to be run, and therefore affects the time measurement. This is widely referred to as the *probe effect*. Recent MBA techniques trace time at the hardware level, rather than injecting measurement function calls in the source code, thus avoiding inaccuracies in time measurements [Bernat et al., 2002]. The main assumption behind MBA is that the highest observed execution time, i.e., the High Water-Mark Time (HWMT), is a good estimate of the WCET provided that (1) the analysis is performed in a realistic operational setting, and (2) the analysis appropriately covers the input space of the RTES. This last point is crucial to ensure that the analysis runs the system on the worst-case inputs that

in turn lead the task to execute in its worst-case path. Being based on measurement, the estimates provided by MBA can be too optimistic, underestimating the WCET. For this reason, a percent margin is usually added to estimates obtained by MBA, but this comes at the cost of a possible overestimation [Kirner et al., 2004].

- **Hybrid Measurement-Based WCET Analysis (HMBA).** This approach combines SA with MBA, with the goal of balancing the trade-off between SA overestimation and MBA underestimation. HMBA divides the task source code into segments (*instruction blocks*), separated by *instrumentation points*. The execution time of each block is then measured at each instrumentation point, and recorded into a *trace*. The task WCET is then obtained through SA, where the execution times in the trace are used in place of estimates derived from hardware models. Usually each instruction block envelops a single loop, so that execution times in the trace can be combined without using pure SA techniques that overestimate tasks WCET. However, the main assumption behind HMBA is that the execution time of each instruction block has been measured for its longest possible loop. This is hard to ensure in general, even though there have been successful attempts at using Genetic Algorithms (Section 2.4.2.2) to generate input data that provides reliable WCET estimates of instruction blocks [Wegener and Mueller, 2001].
- **Statistical WCET Analysis (STA).** This approach uses statistical methods on a sample set of task execution times to estimate the WCET under a given interval of confidence. STA is based on the Extreme Value Theory (EVT), an approach originally meant to analyze the risk of rare events by studying the tail behavior of a distribution [Beirlant et al., 2006]. The main assumption behind STA is that the WCET can be modeled as a random variable with Gumbel Max distribution, as it often happens for worst-case measures in EVT [Edgar and Burns, 2001].

2.1.3 Simulation in RTES

Scheduling analysis techniques are useful for verifying RTES, especially at design-time when the implementation is not yet available. However, such techniques require restrictive assumptions on the task set, for instance tasks being independent or periodic. For this reason, they face severe limitations when applied to large and complex RTES, where concurrent, inter-dependent tasks are run on multi-core platforms with preemptive scheduling policies. In such systems, these verification techniques are complemented with testing. However, testing in RTES has to account for the system complexity in software, hardware, and the environment. For this reason, it is common in RTES to perform a specific kind of testing at early stages of system development, when details about the hardware platform and the environment have been established, but physical components and implementation are not available yet. In the context of RTES, this type of testing is often referred to as *simulation* [Broekman and Notenboom, 2003], as it takes place at different stages of the system development, where implementation, computing platform, and external hardware are not fully available. Since the behavior of most RTES can be seen as a control loop, these simulations are known as *in-the-loop* simulations, depending on the level of detail they run at. There exist four main types of in-the-loop simulation, hereby described.

- **Model-in-the-Loop (MiL).** This approach consists in simulating the RTES software, hardware and environment to ensure that the system complies with its specification. MiL simulation is based on capturing the system behavior in *behavioral model* models, and therefore is mostly used in the context of Model-based Testing (Section 2.3.1). These models are run in environments simulating both the computational and external hardware, in order to check the RTES compliance with requirement specifications. MiL simulation mostly investigates functional aspects of the system, as a precise performance evaluation is left at further stages, when the physical hardware is available [Lindlar et al., 2010].

- **Software-in-the-Loop (SiL).** MiL simulation can also be extended from models to executable code in order to have a more thoughtful evaluation of the system behavior, as usually the models do not capture implementation details. In SiL simulation, the system software, rather than a model, is run on a development platform that simulates the RTES hardware and environment [Kruse et al., 2009].
- **Processor-in-the-Loop (PiL).** At development stages when the computational hardware of the RTES is available, the system software can be run on a real computing platform in an environment where the external hardware, such as sensors and actuators, and environment are simulated. Running the system at the PiL level can reveal faults caused by code compilers or by the processor architecture that are overlooked at MiL and SiL level [Francis et al., 2007].
- **Hardware-in-the-Loop (HiL).** Finally, when both the computing and the external hardware are available, the RTES can be run on a real platform where only the external environment is simulated, possibly through the use of mathematical models describing continuous or discrete phenomena. HiL simulation is able to reveal faults in the low-level hardware services, such as I/O operations of sensors and actuators [Short and Pont, 2008].

2.2 Model-driven Engineering (MDE)

One of the basic principles behind Software Engineering is raising the level of abstraction when reasoning about software. The idea is to eliminate complexity that is not inherent in software artifacts by abstracting away non-fundamental aspects. Reducing complexity of a certain task has indeed shown to have a positive impact upon software productivity. This is reflected by the fact that, in productivity models, the software cost metrics take into account complexity together with resources and personnel [Fenton and Pfleeger, 1998].

To address the need of reducing software development time and costs, Model-driven Engineering (MDE) rose in the last years as an approach to Software Engineering aimed at handling software complexity through abstractions. Specifically, the goal of MDE is to improve software productivity by using models as the principal way to raise the level of abstraction of a system [Schmidt, 2006]. The cornerstones of MDE are usually summarized in four aspects: (1) models representing real-world elements, (2) metamodels describing the structure of models, (3) languages enabling the formal definition of models and metamodels, and (4) transformations between languages [Favre and Nguyen, 2005].

MDE factorizes software complexity into different levels of abstraction and concern, from high-level conceptual models down to individual aspects of deployment platforms. To do so, MDE combines general-purpose with domain-specific languages to define high- and low-level models respectively, and uses model transformation engines to automatically transform the former into the latter.

2.2.1 Models and Metamodels

The word “model" derives from the Latin “modulus", that can be translated as *pattern*, *rule*, or *example to be followed*. Models are used in several scientific disciplines, ranging from biology, to chemistry and physics. Even though the meaning of *model* can vary across disciplines, models all share a common characteristic: a model is a simplification of a physical system, denoting a particular viewpoint of the system to control it for a given purpose [Apostel, 1961]. Specifically, a model is a *sound abstraction* of an *original* [Stachowiak, 1973]. Being an abstraction means that a model retains a relevant selection of the original's properties with respect to its context and the concerns of the model user. Being sound means that a model can be used in place of the original for analyzing, inferring, or predicting properties of the original.

Models are usually distinguished between *descriptive* and *prescriptive* [Ludewig, 2003]. Descriptive models are intended to mirror an existing original and its phenomena, while prescriptive models are used as a specification to create an original. While the former are mostly used in natural sciences or reverse engineering, Model-driven Engineering heavily relies on prescriptive models. Indeed, most of the software models, such as design, process, and information flow models, are used to drive development as they are the essential part of the system specification.

There is no universal agreement on a precise definition of a model. However, the experience from practitioners and academics established over the years a common sense on the relationship between a model and what it models, and the notions of metamodel and model instantiation. Since a model is basically a representation operating an abstraction over its original, then the relationship between a subject and its model is a fundamental aspect in the theory of models. A model is either a *token model* or a *type model* [Kühne, 2006]. We illustrate this distinction with the example of a road map depicting cities connected through roads.

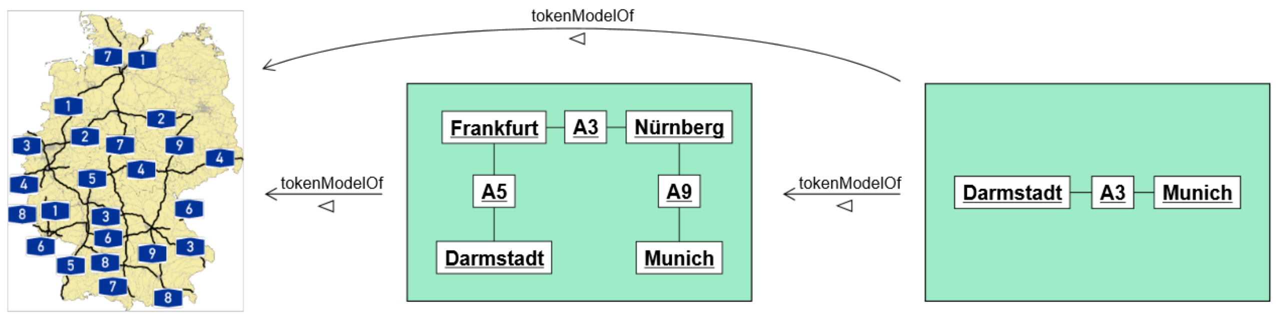
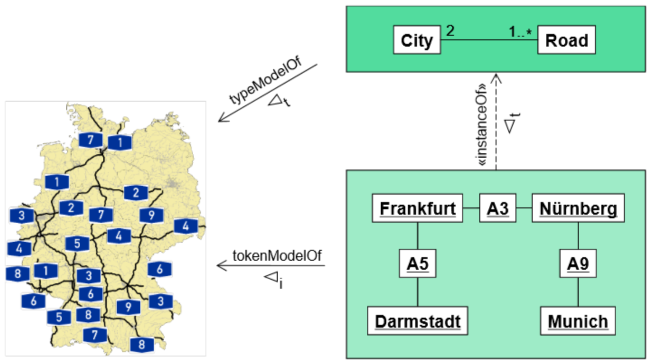


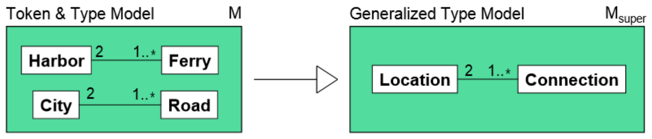
Figure 2.4. Example of Token Models [Kühne, 2006]

Token models directly represent originals by capturing *singular* (as opposed to *universal*) aspects of the original elements. In Figure 2.4, the map on the left is an original, while the box at the center is a token model of it. The token model associates one model element, e.g., *Frankfurt*, to exactly one original element, e.g., the city of Frankfurt in the map. In this sense, they provide a one-to-one mapping between the model and the original properties. Note that the model abstracts away some properties of the original:

only four cities and three roads are depicted in the model. The box on the right is another token model of the map containing even fewer details: only two cities and one road are depicted there. Also note that the model on the right can in turn be seen as a token model of the model in the center.



(2.5.1) Type model of a token model



(2.5.2) Generalized type model of a type model

Figure 2.5. Examples of a type model and its generalized type model [Kühne, 2006]

Type models classify, or conceptualize, the original elements by capturing *universal* aspects of such elements in a many-to-one mapping. In Figure 2.5.1, the box at the top contains the two elements *City* and *Road*, that classify the elements of the original by stating the universal nature of maps: roads connect two cities, and cities are connected by one or more roads. Note that many elements in token models are mapped to a single element in a type model: *Darmstadt*, *Frankfurt*, *Nürnberg*, and *Munich* are all mapped to *City*, while *A5*, *A3*, and *A9* are mapped to *Road*. Specifically, type models provide a *classification* of token models, in the sense that they specify a universal for equivalent items. For this reason, the token model at bottom right of Figure 2.5.1 is an *instance* of type model at the top. The process of classification can in turn be extended to type models when one wants to infer even more general elements from existing classifications. In Figure 2.5.2, the box on the left contains another type model specifying that each *Ferry* connects two harbors, and each *Harbor* is connected through one or more ferries. This type model is conceptually very similar to the one of cities and roads, provided that one abstracts away from the physical support of terrestrial and maritime connections. Therefore, the entities in both type models can be pairwise depicted into single super-concepts, as in the box on the right of Figure 2.5.2. Each ferry and road can be seen as a *Connection* connecting two locations, and each *Location* is connected through one or more connections. Specifically, generalized type models provide a *generalization* of type models, in the sense that they extend their universal concepts. The generalization relationship is usually depicted with an arrow whose head is an empty triangle ($\triangle$).

Starting from the concepts described above, one can provide a mathematical formalization of the concept of model [Kurtev et al., 2006] through the definitions below.

Directed Multigraph. *A directed multigraph $G = (N_G, E_G, \Gamma_G)$ is a triple where:*

- *N_G is a set of nodes*
- *E_G is a set of edges*

- *$\Gamma_G : E_G \rightarrow N_G \times N_G$ is a function that maps edges to pair of nodes*

Note that Γ_G can possibly be non-injective, therefore allowing different edges to connect the same pair of nodes.

Model. *A model $M = (G, \omega, \mu)$ is a triple where:*

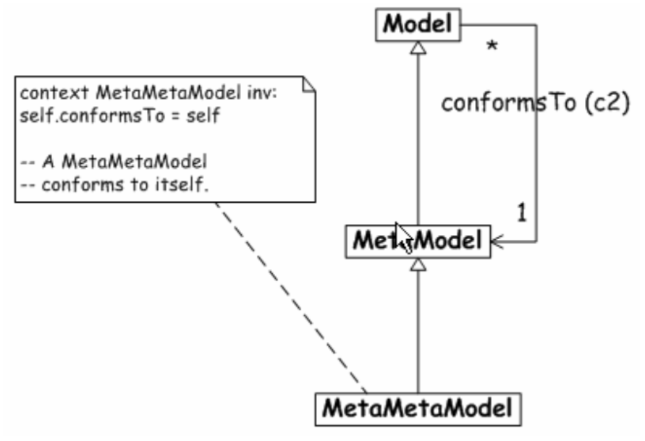
- *$G = (N_G, E_G, \Gamma_G)$ is a directed multigraph*
- *ω is a reference model associated to its directed multigraph $G_\omega = (N_{G_\omega}, E_{G_\omega}, \Gamma_{G_\omega})$*
- *$\mu : N_G \cup E_G \rightarrow N_{G_\omega}$ is a function that maps nodes and edges of G to nodes of G_ω*

The relationship between a model and its reference model is called *conformance*, and specifies that each element in a model corresponds to an element in its reference model.

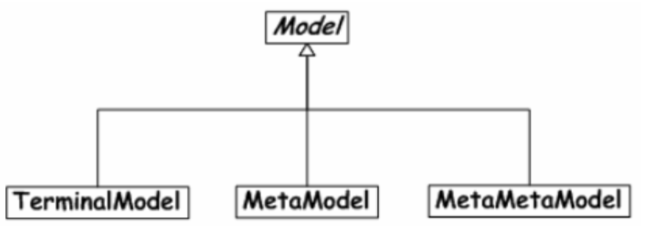
Metametamodel. *A metametamodel $M_3 = (G_3, \omega_3, \mu_3)$ is a model that is the reference model of itself, i.e., $\omega_3 = M_3$.*

Metamodel. *A metamodel $M_2 = (G_2, \omega_2, \mu_2)$ is a model such that its reference model is a metametamodel.*

Terminal Model. *A terminal model $M_1 = (G_1, \omega_1, \mu_1)$ is a model such that its reference model is a metamodel.*



(2.6.1) Organization of the metamodeling stack



(2.6.2) Classification of models as terminal models, metamodels, and metametamodels

Figure 2.6. Metamodeling stack and classification of models [Kurtev et al., 2006]

Figure 2.6.1 depicts the organization of models, metamodels, and metametamodels in terms of the conformance relationship. Such organization is usually referred to as *metamodeling stack*. In this figure, the conformance relationship is denoted by *conformsTo* or *c2*, and details how a model conforms to one metamodel, which in turn is the archetype of one or more models that conform to it. A metamodel conforms to one self-conforming metametamodel. The definitions above also imply the classification of models as in Figure 2.6.2, that shows that terminal models, metamodels, and metametamodels are all instances of a generic *Model* type.

Besides models and metamodels, Model-driven Engineering approaches also extensively rely on Model Transformations and Domain Specific Modeling (DSM) as ways to automate steps in the system development, and to tackle software heterogeneity and complexity. These two concepts are not entirely relevant for the scope of the thesis, and are only briefly discussed for the sake of completeness.

MDE strongly revolves around the concept of models, that by nature are expensive and difficult to build. However, the formal definition of a metamodeling stack enable the (semi-)automated manipulation of models through *model transformations*. One of the most common definitions of model transformation implies the automatic generation of a target model from a source model, according to a transformation definition [Kleppe et al., 2003]. A typical model transformation is based upon a *transformation specification* detailing the mapping of elements from a *source metamodel* into elements of a *target metamodel*. When executing the model transformation, an *input model* conforming to the source metamodel is transformed into an *output model* conforming to the target metamodel, following the rules of the specification. Model transformation allows to automate the generation and manipulation of models, which is error-prone if done by hand. One of the main use of model transformations is to generate source code from models upon the use of target metamodels which are intended to be manipulated through text. The automatic generation of source code from system models allows developers to focus on design, rather than implementation, and to minimize the effort of maintaining consistency through artifacts at different levels of abstractions.

However, model transformation by itself requires an input model, that has to be created by humans. Designing a model of a large and complex system can be challenging, because it is hard to capture all its different aspects. A basic principle behind the solution of several engineering problems is the *divide-and-conquer* approach: given a problem, first divide it into easier sub-problems, then solve them one at a time, and finally aggregate the solutions of the sub-problems to generate the solution of the original problem. In MDE, the same approach is applied to software development by dividing the design activity into several areas of concerns, each focusing on a specific aspect of the system. In this way, it is possible to reason over software specifications at a higher level of abstraction, and to provide partial specifications which are easier for experts to manage because they are closer to their domains. This approach is known in MDE as DSM, a methodology that makes systematic use of Domain Specific (Modeling) Languages (DSL, or DSML) to represent artifacts of a system pertaining to a given domain. DSL are languages meant to support higher-level abstractions than General Purpose Languages (GPL), so they require less effort and fewer low-level details to specify a system. The separation of concerns behind DSM does not only allow a better management of software complexity by humans. Indeed, DSM also fully exploits the idea of code generation through model transformations by providing modeling languages easier to use and understand. As a consequence, the joint use of DSM and model transformations increasingly shifts the focus of software development into the creation of models rather than code.

2.2.2 Standards for Model-driven Engineering

The principles of Model-Driven Engineering provide conceptual foundations of the approach, but they can applied in different ways. There exist several implementations of such principles that standardize the manipulation of models, providing tool support for MDE approaches. These tools provide Integrated Development Environments (IDE) with frameworks for repository management, model transformation, and so on. In the rest of this chapter, we briefly discuss the Model-Driven Architecture (MDA) in Section 2.2.2.1 as the MDE reference implementation for the Unified Modeling Language (UML, Section 2.2.2.2). An extensive description of MDE standards, MDA and UML falls beyond the scope of this thesis. Nonetheless, introducing UML is necessary to describe the UML Profile for Modeling and Analysis of Real-Time Embedded Systems (UML/MARTE, Section 2.2.2.3) that has been used in this thesis to formalize the key abstractions of stress testing.

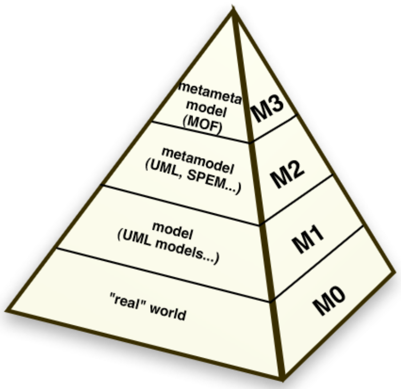
2.2.2.1 Model-Driven Architecture (MDA)

The most common implementation of the MDE principles is the Model-Driven Architecture (MDA) defined by the Object Management Group (OMG) in 2001 [Kleppe et al., 2003]. The Model Driven Architecture is based upon three cornerstones [Soley et al., 2000]. (1) First, MDA proposes a pyramidal construction of models, organized in four layers as in Figure 2.7.1. Artifacts in the bottom level *M0* represent actual systems in the real world. Those are modeled by token models in the level *M1*, which are in turn compliant to metamodels in the level *M2*. The top level *M3* consists of the Meta-Object Facility (MOF) as the reference self-conforming metametamodel used to specify all the metamodels in MDA. (2) Second, MDA proposes a vision of software development structured in six main steps, each centered around a specific model as in Figure 2.7.2. System requirements are initially collected into a Computation Independent Model (CIM), independently from computational notions. Then, the CIM is transformed into a Platform Independent Model (PIM) that describes the CIM in computational terms independently from specific implementation technologies. The PIM is merged with a Platform Description Model (PDM) containing information on the platform where the system will be deployed to form a Platform Specific Model (PSM). The PSM links the PIM specification with information about a specific platform and can finally be transformed into executable source code. (3) Third, MDA proposes the Unified Modeling Language (UML) as the reference language to describe models [Booch et al., 2000].

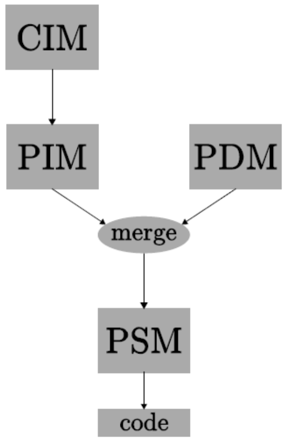
2.2.2.2 Unified Modeling Language (UML)

The Unified Modeling Language (UML) is a general-purpose modeling language, designed to provide a standard way for visualizing software systems. UML has been initially developed in 1998 as a graphical notation, and evolved to include a formal specification upon its adoption in the MDA in 2007. Since its creation, UML has become an international standard for defining models of software systems. As of version 2.4.1, UML defines 14 types of diagrams, divided into two main classes: *structural* and *behavioral* diagrams (Figure 2.8). A thorough description of UML and its diagram types falls outside the scope of this thesis. Nonetheless, we briefly introduce the UML diagram types, especially focusing on sequence diagrams. This is because sequence diagrams are the main way to visualize concurrency in software, and therefore they are of primary importance to enable reasoning over performance properties in the context of real-time systems.

- **Structural Diagrams** represent the *static* aspect of the system, i.e., the set of parts composing its architecture. Structural diagrams describe the system in terms of components at different levels of abstraction, focusing on their dependencies. There exist seven types of structural diagrams.



(2.7.1) The MDA metamodeling stack, organized as a pyramid [Thirioux et al., 2007]



(2.7.2) Vision of software development in MDA [Miller et al., 2003]

Figure 2.7. Two cornerstones of the MDA: the pyramidal metamodeling stack and the software development vision

- **Class Diagrams** are the most common diagrams in UML, and depict the key entities in the system as *classes*, i.e., object types, their properties as *attributes*, and their relationships as *associations*.
- **Component Diagrams** display the structural relationship of components, i.e., sets of classes that collaborate to realize certain features and communicate through interfaces.
- **Object Diagrams**, also referred to as *Instance Diagrams*, show relationships between actual objects in the system, instanced from classes using real data. The most important abstraction in object diagrams defines *active objects* as an object that owns a process or thread, and that can initiate control activity. For this reason, active objects are the ones encapsulating the behavior of the system, and are further described in behavioral diagrams. Objects that are not active are said to be *passive*.
- **Profile Diagrams** describe UML *profiles*, i.e., extensions to the language that allow adaptation to different platforms and domains.
- **Composite Structure Diagrams** show the internal structure of classes in terms of functions and variables.
- **Package Diagrams** represent groups (*packages*) of elements, such as classes and components, under a common namespace.
- **Deployment Diagrams** show how the software components of the system are allocated, i.e., *deployed*, into hardware components.

• **Behavioral Diagrams** represent the *dynamic* aspect of the system, i.e., the interactions between parts of the system that define functionalities and runtime operation. Behavioral diagrams describe the system in terms of states of its components, focusing on changes in such states. There exist seven types of structural diagrams.

- **Use Case Diagrams** are the most common behavioral diagrams in UML, and provide a high level description of the system functionalities (*use cases*) from the viewpoint of external en-

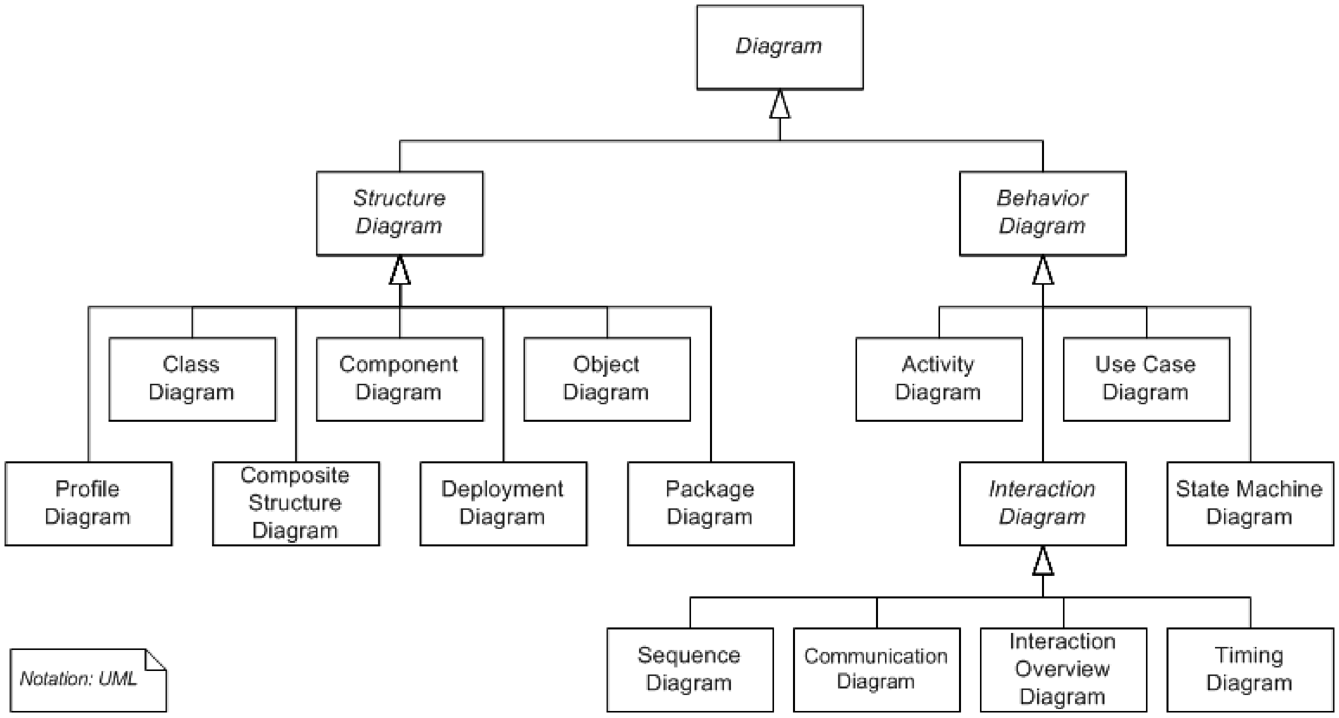
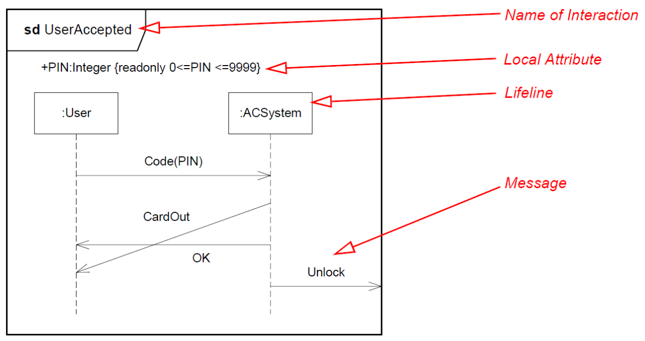


Figure 2.8. Taxonomy of UML 2.4.1 diagrams

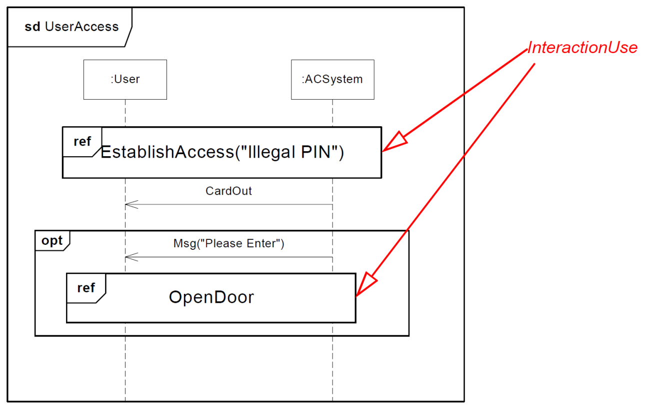
tities that interface to it (*actors*).

– **Activity Diagrams** model the system computational and organizational processes through flowcharts of stepwise activities and actions.
– **State Machine Diagrams** implement the concept of Finite States Automaton in UML, representing the system behavior as a series of events that determine transitions through states.
– **Interaction Diagrams** are a subset of behavioral diagrams that emphasize the data and control flow among elements of the system. There exist four types of interaction diagrams.
  ∗ **Communication Diagrams** model the interactions between system objects in terms of sequences of messages.
  ∗ **Interaction Overview Diagrams** are particular activity diagrams where each activity is pictured as a frame representing a nested interaction diagram.
  ∗ **Timing Diagrams** model the change in state of system elements over time.
  ∗ **Sequence Diagrams** are the most common interaction diagrams in UML, and show the execution order of system processes, highlighting their interoperation. Sequence Diagrams depict the entities operating concurrently as vertical *lifelines*, and *messages* exchanged between them as horizontal arrows, entailing the order in which such messages occur.

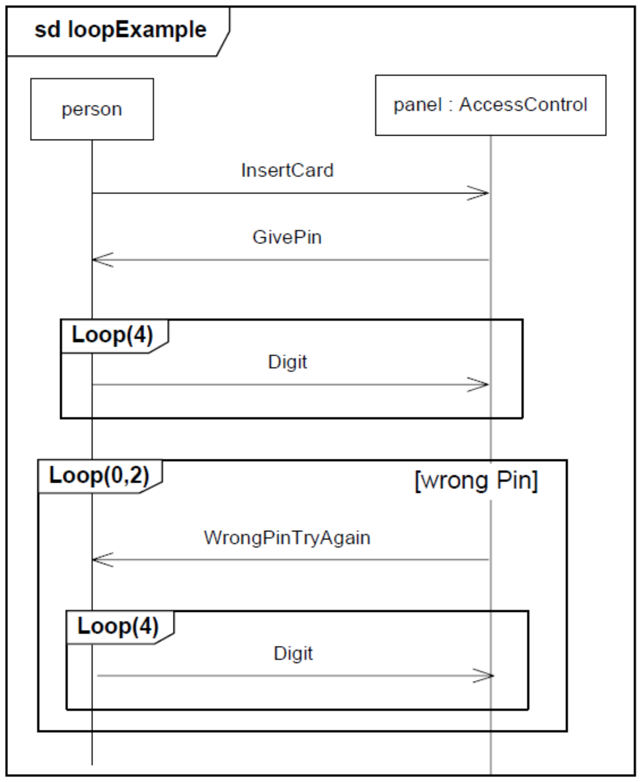
Figure 2.9 illustrates the graphical notation of sequence diagrams through examples. Figure 2.9.1 shows a sequence diagram describing an interaction scenario in an Access Control System (*ACSystem*) that regulates electronic door locks via access cards and PINs. In this interaction, labeled as *UserAccepted*, a *User* interacts with the system to unlock a door upon inserting the access card with its PIN.



(2.9.1) Lifelines and Messages in sequence diagrams



(2.9.2) Interaction Uses in sequence diagrams



(2.9.3) Combined Fragments in sequence diagrams

Figure 2.9. Graphical notation of Sequence Diagrams [OMG, 2011b]

The example shows three messages labeled as *Code(PIN)*, *CardOut*, and *OK*, exchanged in this order by two lifelines of types *User* and *ACSystem*. The sequence diagram also includes a *Local Attribute* of type Integer, representing the PIN being inserted by the user. Once the user inserts the card code, the system asynchronously sends the messages *CardOut* and *OK*, and finally sends a fourth *Unlock* message to an undisplayed entity in the environment. Interaction diagrams, and in particular sequence diagrams, also allow the definition of *Interaction Fragments*, which are named elements representing an interaction unit. There exist several types of interaction fragments, among which *Occurrence Specifications*, *Execution Specifications*, *Interaction Uses* and *Combined Fragments* are the most used in sequence diagrams.

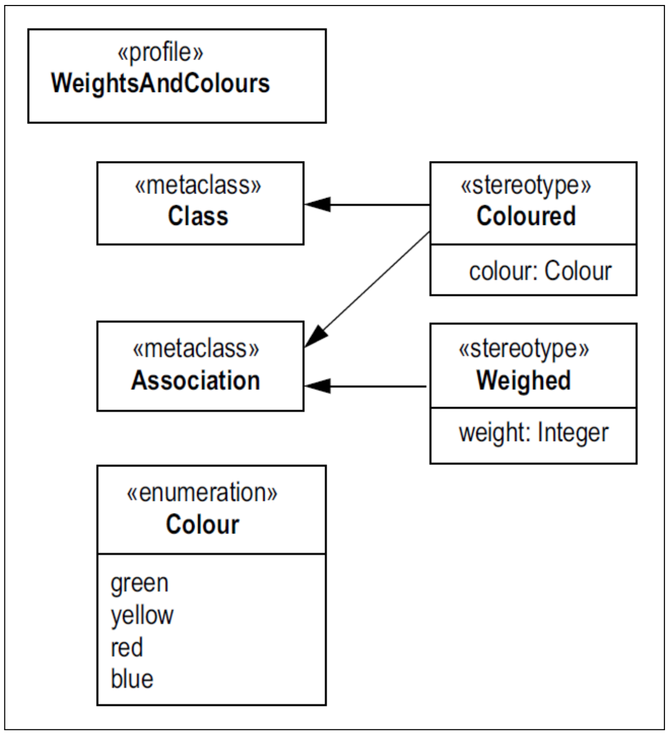
- **Execution Specifications (executions, or activations)** represent a period of time in a lifeline where the participant entities either (1) execute a unit of behavior, (2) send a signal to another entity, or (3) wait for a reply message from an entity. Executions specifications are usually depicted in lifelines as rectangles. Occurrence Specifications (often simply called *occurrences*) represent a moment in time at the beginning or end of a message, or at the beginning or end of an execution.
- **Occurrence Specifications (or occurrences)** appear on exactly one lifeline, and are ordered along such lifeline. Note that occurrence specifications have no notation, as they are represented by a point at the beginning or end of a message or execution.
- **Interaction Uses** allow to reference interactions: Figure 2.9.2 shows the interaction *UserAccess*

that refers to the externally defined interactions *EstablishAccess* with argument *Illegal PIN*, and *OpenDoor*. Interaction uses are commonly used to simplify the notation of large and complex sequence diagrams by allowing the reuse of already defined interactions.

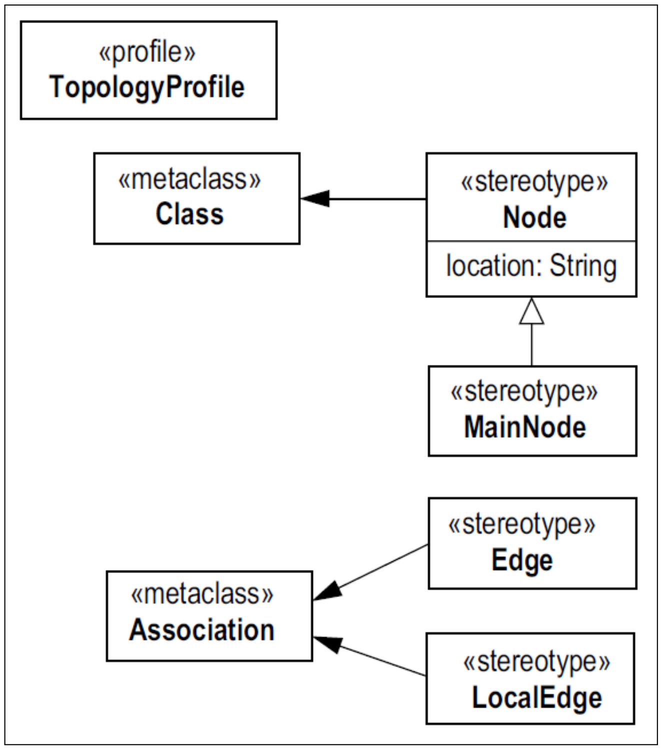
- **Combined Fragments** define combinations or expressions of interaction fragments. The semantic of combined fragments is defined by an *interaction operator*. Figure 2.9.3 shows an example of a *Person* inserting his card into the system to unlock a door. After receiving the *GivePIN* message by the *AccessControl*, the user inserts the four digits of his PIN one at a time. This is modeled by a combined fragment with the *Loop* operator, stating that the body of the loop is repeated four times. Combined fragments can also have *Interaction Constraints* in the form of guards. If the user inserts the wrong code, the *Wrong PIN* guard evaluates to true, so that the user can insert the code two more times. Note that, as in this last case, combined fragments can be nested.

UML is a General Purpose Language designed to be used in software development at every stage, from high-level specification, e.g., with use case diagrams, to low-level implementation details, e.g., with deployment and state machine diagrams. The universality of UML makes it suitable for a variety of purposes, but comes at the cost of flexibility. Indeed, UML cannot always provide the abstraction level developers need to model software in every domain [Atkinson and Kühne, 2007]. In MDE, this problem is addressed with the use of Domain Specific Languages, but UML also includes the possibility to define *profiles*, a built-in mechanism to tailor the language for specific needs. Specifically, profiles allow the extension of UML metaclasses by providing additional semantics through two main constructs: *stereotypes* and *tagged values*. Stereotypes define extensions of existing UML metaclasses, enabling the use of domain-specific notation that provides additional semantic for the extended metaclass. Stereotypes are defined by a name and by the set of metamodel elements they extend. Tagged values are meta-attributes attached to a metaclass of the metamodel extended by a profile. Tagged values have a *name* and a *type*, and are associated to a specific stereotype. We further illustrate these concepts through the example in Figure 2.10.

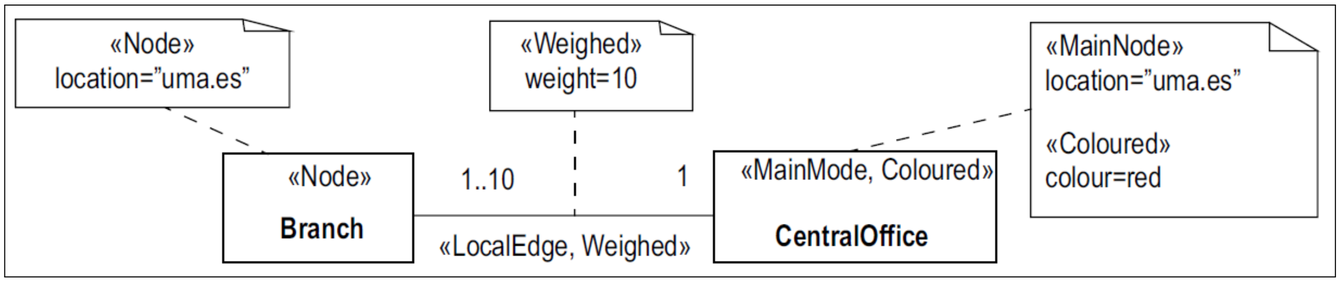
Figure 2.10.1 shows the *WeightsAndColours* profile that extends UML proving modeling support for the concepts of weights and colors, with the possibility to specify the color of colored elements, and the weight of weighed elements. *WeightsAndColours* defines the two stereotypes *Colored*, extending the UML metaclasses *Class* and *Association* and *Weighted*, extending the metaclass *Association*. Stereotypes are graphically visualized in boxes labeled *stereotype*. This means that, when applying the profile, classes and associations can be colored, i.e., stereotyped *Colored*, and associations can also be weighted, i.e., stereotyped *Weighted*. The stereotype *Colored* has a tagged value named *color* specifying that each colored element has a specific color, chosen from an *Enumeration* of four. Similarly, the stereotype *Weighted* has a integer tagged value named *weight* that represents the weight of the stereotyped association. Tagged values are formally specified as attributes of the class defining the stereotype. Figure 2.10.2 shows *TopologyProfile*, another example of UML profile extending UML with concepts such as *Node* and *Edge*. Figure 2.10.3 finally shows a class diagram with classes and associations stereotyped with both these profiles. Specifically, the diagram shows a *Branch* node in a weighted, *LocalEdge* association with a *CentralOffice* colored *MainNode*. In the example, the tagged values are represented within UML *notes*.



(2.10.1) Example of a UML profile concerning colors and weights



(2.10.2) Example of a UML profile concerning nodes and edges



(2.10.3) Example of application of the UML profiles

Figure 2.10. UML Profiles definition and usage showed through an example [Fuentes-Fernández and Vallecillo-Moreno, 2004]

2.2.2.3 UML Profile for Modeling and Analysis of Real-Time Embedded Systems (UML/MARTE)

UML has been used for long time to model Real-Time Embedded Systems [Selic, 1998], but it is not flexible enough to be effectively applied in complex real-time systems. As discussed in Section 2.2.2.2, profiles are meant to tailor UML to specific domains, providing high level concepts to support software modeling. When it comes to RTES, the UML profile for Modeling and Analysis of Real-time Embedded Systems (UML/MARTE, in short MARTE [OMG, 2011a]) is the most acknowledged and used by practitioners. MARTE is an OMG standard defined in 2011 to replace its predecessor UML profile for Schedulability, Performance, and Time (SPT), aligned with UML v1.x [OMG, 2005].

The specification of MARTE defines the profile in two steps. The first step consists of defining the concepts related to one specific concern in RTES. These concepts are referred to as *domain elements*, e.g., abstractions to model time, scheduling, or non-functional properties. The domain elements are gathered in the *domain model*, which is formalized through the definition of a meta-model and the detailed semantics descriptions of each of its elements. The second step in the definition of MARTE consists of the actual formalization the UML profile, referred to as *UML representation*. In particular, the specification of MARTE maps the concepts introduced in the domain model to UML stereotypes, tagged values, specific notations, and Object Constraint Language (OCL) rules. Note that abstractions in the domain model are grouped in *packages*, while the extensions in the UML representation are grouped in *sub-profiles*. Therefore, packages in the domain model map into sub-profiles in the UML representation. Also note that sub-profiles in the UML representation can also be grouped in packages, which should not be confused with the packages of domain models.

Figure 2.11 shows the architecture of MARTE, which consists of four main packages, each grouping several sub-profiles. MARTE revolves around the main concept of providing support for both design and analysis of RTES. These two development activities are supported with the abstractions defined in *design model* and *analysis model* packages [Gerard and Selic, 2008], respectively. Due to its completeness and level of detail, it is beyond the scope of this thesis to thoughtfully examine MARTE. Nonetheless, we provide an overview of its architecture, especially focusing on the domain model packages containing abstractions for quantitative analysis and resource modeling. This is because the sub-profiles associated to these packages provide frameworks for collecting information pertaining to schedulability and performance analysis, and to model resources in computational platforms. These two concepts are essential when it comes to stress testing, that entails finding worst-case scenarios with respect to some performance requirement. Indeed, such worst-case scenarios are characterized by the way concurrent software tasks are scheduled by the Real-Time Operating System, and the schedules in turn depend on the runtime status and properties of the computational platform.

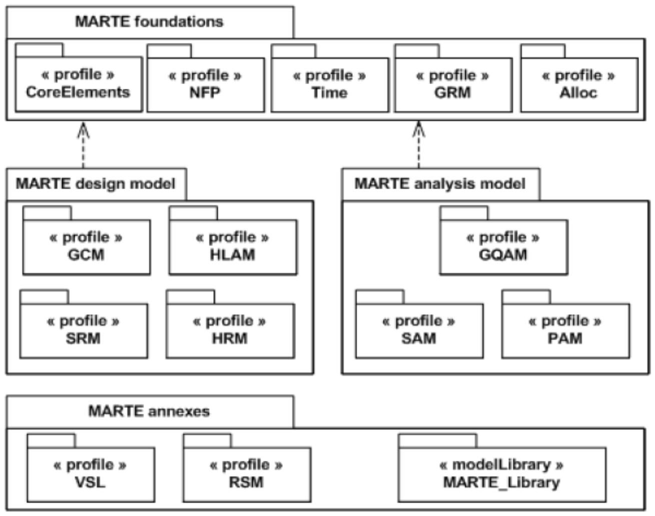


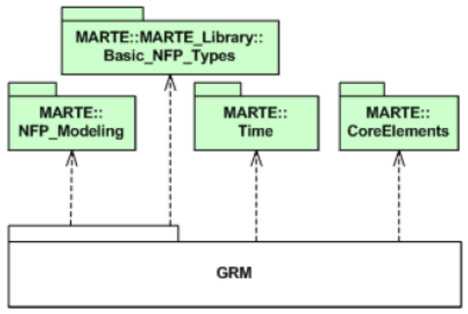
Figure 2.11. UML/MARTE Architecture [OMG, 2011a]

- **MARTE foundations** contains the abstractions shared by the two main packages, *MARTE design model*, and *MARTE analysis model*. Therefore, this package defines concepts used in both analysis and design of RTES, such as abstractions for representing time, concurrent resources, and quality of service. *MARTE foundations* is structured in five sub-profiles.
  - **CoreElements** contains the basic elements used for structural and behavioral modeling of RTES. The domain model of this profile consists of the two packages *Foundations* and *Causality*, containing abstractions for model-based design and analysis of RTES, respectively.
  - **Non-Functional Properties (NFP)** contains modeling constructs to declare non-functional properties as UML data types, so that they can be attached to standard UML elements. This profile defines concepts to express relationships and constraints among non-functional properties in order to model system non-functional requirements.
  - **Time** supports modeling the notion of time and time-related concepts such as clocks and time events. This profile allows the definition of three time models: *causal/temporal*, for modeling relative ordering of events, *clocked/synchronous*, for modeling time as a discrete succession of instants, and *physical/real-time*, for modeling continuous time.
  - **Generic Resource Modeling (GRM)** contains abstractions to represent computing platforms as sets of resources, possibly organized as a hierarchy, where each resource offers services in response to service requests.
  - **Allocation Modeling (Alloc)** provides support for allocating system functionalities into computational resources, providing a conceptual link between real-time software and the hardware platform that runs it.
- **MARTE design model** refines the concepts defined in *MARTE foundations* from the view-point of RTES design. This package provides domain-specific concepts of real-time applications and components, and software and hardware resources. *MARTE design model* is structured in four sub-profiles.
  - **Generic Component Modeling (GCM)** refines concepts already defined in UML to support modeling component-based RTES.
  - **High-Level Application Modeling (HLAM)** provides modeling concepts for modeling features in RTES at a high level of abstraction. The domain model of this profile defines Real-time Units (*RtUnit*) as the main concurrent entities of a system, and Protected Passive Units (*PpUinit*) as mechanisms to share information among real-time units.
  - **Software Resource Modeling (SRM)** refines the concepts defined in *GRM* to model Application Programming Interfaces (API) for concurrent software, independently from the specific Real-Time Operating System used. The domain model of this profile provides modeling concepts for software resources (*ResourceCore*), concurrent execution contexts (*Concurrency*), resources communication (*Interaction*), and management (*Brokering*). Being RTOS-independent, the concepts in *SRM* have to be complemented with specific modeling libraries implementing OS standards. Such libraries are introduced in the package *MARTE annexes*.
  - **Hardware Resource Modeling (HRM)** refines concepts in *GRM* to model components of hardware platforms, such as processors, memory hierarchies, Application-Specific Integrated Circuits (ASIC), and Programmable Logic Devices (PLD). Note that, while *SRM* provides generic abstractions that have to be complemented with modeling constructs specific to RTOS

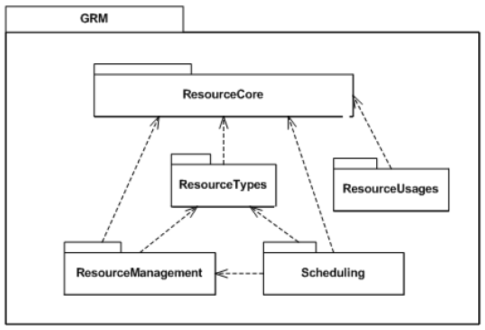
standards, the abstractions in *HRM* do not to need to be further specified. This is because, while there exist a variety of RTOS that differ from each other in several aspects, the differences in hardware platforms for RTES are small enough that can be captured by a single sub-profile, without the need of hardware-specific additional information.

- **MARTE analysis model** represents models from schedulability and performance analysis theories into a UML framework, by refining the concepts defined in *MARTE foundations*. Note that this package does not entail the definition of particular analysis techniques, but rather defines the modeling constructs to enable them. *MARTE analysis model* is structured in three sub-profiles.
  - **Generic Quantitative Analysis Modeling (GQAM)** provides concepts to enable the definition of quantitative analysis in RTES, i.e., the investigation on how the system behavior affects the resources usage. The abstractions in this profile support the definition of techniques aimed at determining the values of *output NFP*, such as deadline misses, response times, and resources utilizations, in terms of *input NFP*, such as, task deadlines, periods, and arrival times.
  - **Schedulability Analysis Modeling (SAM)** refines the concepts defined in *GQAM* to enable model-based schedulability analysis methodologies based on UML. This subprofile provides modeling constructs for attaching quantitative measures to UML models. These measures represent in turn the input for mathematical formalisms used for schedulability analysis, such as extended timed automata, holistic techniques, or Rate Monotonic Analysis (RMA).
  - **Performance Analysis Modeling (PAM)** refines the concepts defined in *GQAM* to enable model-based performance analysis methodologies based on UML. Opposed to *SAM*, this profile focuses on the definition of performance modeling as the probabilistic analysis of temporal properties of RTES. Therefore, both the input and output measures of performance analysis are modeled as statistical values, such as means, deviations and probabilities. Similar to *SAM*, these statistical quantities represent in turn input for performance analysis techniques such as simulations, extended queuing models, and discrete-state models.
- **MARTE annexes** contains complementary cross-cutting modeling constructs that are not organized in the other three packages. *MARTE annexes* is structured in three sub-profiles.
  - **Value Specification Language (VSL)** complements the *NFP* profile by defining a textual language for specifying algebraic and time expressions conforming to an extended system of data types. Indeed, while NFP supports the declaration of non-functional properties as UML data types, *VSL* supports the description of the values for those types.
  - **Repetitive Structure Modeling (RSM)** defines constructs for describing system with a regular structure, i.e., systems with a large number of identical components such as parallel computation systems. This profile defines abstractions to consider structures as repetitions of elements interconnected via regular connection patterns.
  - **MARTE Library** contains guidelines to complement the abstractions in *SRM* in order to model API in specific RTOS. This profile contains modeling libraries with abstractions from the domain of the ARINC 653 [Prisaznuk, 2008], POSIX [Burns and Wellings, 2001] or OSEK/VDX [Lemieux, 2001] standards.

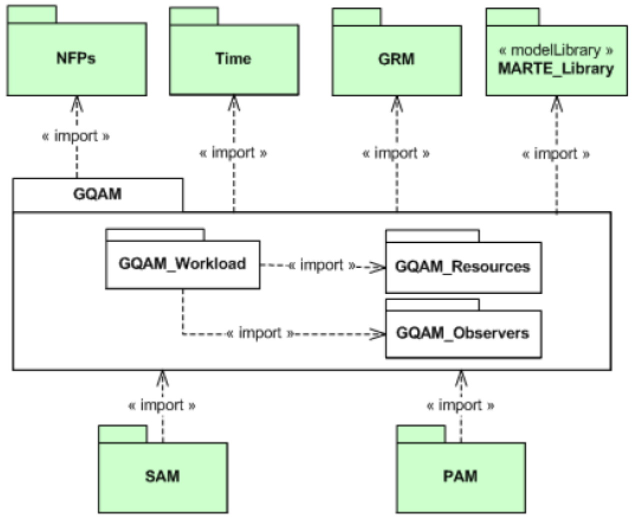
Figure 2.12 shows the architecture of the *GRM* and *GQAM* sub-profiles of UML/MARTE. These



(2.12.1) Dependencies of *GRM*



(2.12.2) Architecture of *GRM*



(2.12.3) Architecture and dependencies of *GQAM*

Figure 2.12. Architectures of the UML/MARTE packages for Generic Resource Modeling and Generic Quantitative Analysis Modeling [OMG, 2011a]

packages contain the stereotypes and attributes which map to the conceptual model of our stress testing approach. Figures 2.12.1 and 2.12.2 show dependencies and architecture of the *GRM* domain model, which is structured in five packages.

- **ResourceCore** defines the basic abstractions for resource modeling, providing constructs to model the system in terms of resources, and services provided by such resources. A *Resource* represents a persistent entity of the system offering one or more *ResourceServices*. Resources have *Instances* at runtime, and can be associated with non-functional properties.
- **ResourceTypes** defines the fundamental types of resources and the services they provide. MARTE defines seven main types of resources.
  - **StorageResource** models resources capable of storing information, such has Hard Disk Drives (HDD) or Rapid Access Memory (RAM).
  - **TimingResource** models resources centered around the notion of time, such as clocks.
  - **SynchResource** models resources arbitrating concurrent execution flows, such as semaphores.
  - **ComputingResource** models physical or virtual processing devices capable of storing and executing program code, such as Central Processing Units (CPU).
  - **ConcurrencyResource** models resources capable of executing concurrently with others, such as threads or processes in a concurrent environment.
  - **DeviceResource** models external resources that require system services to operate, such as peripheral devices.

  - **CommunicationResource** models terminal entities (*CommunicationEndPoint*), and channels (*CommunicationMedia*) involved in a communication, such as system peripherals and buses.
- **ResourceManagement** defines resource management services in two main concepts. First, *ResourceManager* models a resource responsible for creating, maintaining, and deleting resources according to a *ResourceControlPolicy*. Second, *ResourceBroker* models resources responsible for allocation and de-allocation of resource instances to clients, according to an *AccessControlPolicy*.
- **ResourceUsages** models the usage of resources providing concepts such as demand of resources (*UsageDemand*) and amount of resources used (*UsageTypeAmount*).
- **Scheduling** defines abstractions to model how the system behavior is arranged at run-time in terms of the execution order of tasks. This package defines a *ProcessingResource* as a kind of resource capable to process information, such as a *ComputingResource*, *CommunicationMedia*, or *DeviceResource*. Then, it defines a *Scheduler* as a *ResourceBroker* that brings access to *ProcessingResources* following a certain *SchedulingPolicy*. Finally, it defines a *SchedulableResource* as a particular *ConcurrencyResource* that can be granted computational power by a *ProcessingResource* according to *SchedulableParameters*.

Figure 2.12.3 shows the dependencies and the architecture of *GQAM* domain model. The main abstraction of the package is the *AnalysisContext*, defined in terms of operations triggered over time by events (*WorkloadBehavior*). and the container of resources that perform such operations (*ResourcesPlatform*). *GQAM* is structured in three packages.

- **Workload** defines the concepts of system workload and behavior. A *WorkloadBehavior* is a set of system behaviors (*BehaviorScenario*), triggered by a set of events (*WorkloadEvent*), and consisting of sequences of operations (*Step*). Each *Step* is allocated into a *SchedulableResource*, and can be acquiring (*AcquireStep*) or releasing (*ReleaseStep*) a resource to perform its operations. For this reason, the abstraction *BehaviorScenario* inherits from *ResourceUsage*, since each behavior is characterized by a demand of resources. Note that a *BehaviorScenario* is conceptually similar to a task in scheduling analysis (Section 2.1.1).
- **Resources** refines the concept of resource defined in *GRM* by defining the *ResourcesPlatform* abstraction, which represents a container for the resources used to perform a *BehaviorScenario* defines two types of resource: *ExecutionHost*, a processor that executes operations specified in the model, and *CommunicationsHost*, a hardware link between devices to transmit messages through a *CommunicationChannel*.
- **Observers** defines the concept of *TimedObserver* as an entity collecting performance measures on an interval of time between two specific events.

Effectively applying the UML/MARTE concepts in industrial contexts is a challenging task that is complicated by two main factors [Iqbal et al., 2012]. (1) MARTE is a very large profile that accounts for a variety of performance-related aspects in RTES. Indeed, the profile is meant to provide modeling support in all the lifecycle phases of RTES, ranging from design to performance analysis and verification. Nonetheless, for practical use, one often needs only a subset of the abstractions defined in the profile. However, (2) MARTE is a relatively young standard, and there exists little published research providing guidelines on how to apply its concepts, i.e., on how to identify the relevant abstractions for a particular kind of analysis. For these reasons, there is the need to define frameworks to guide practitioners in applying MARTE. Typically, a methodology is needed which identifies the subset of MARTE that best fits the performance analysis to be carried out. This is especially true when it comes to performance stress testing. However, few sources are available that highlight relevant concepts in the profile for identifying worst-case scenarios with respect to performance requirements.

2.3 Software Testing

Software testing is an investigation conducted by system developers to systematically evaluate the System Under Test (SUT) by observing its execution [Myers et al., 2011]. It is acknowledged as one of the most critical activities in the software development process, as studies have shown that testing typically takes more than 40% of the total development time [Boehm, 1981]. Even though there exist a large number of strategies for software development, testing is an essential part in each of them. The archetype of such strategies is the *Waterfall Model*, which is often represented as a *V-Model* (Figure 2.13) [Forsberg and Mooz, 1991]. The left side of the V shows the top-down steps where software requirements are progressively refined into more detailed and technical representations of the system, down to its source code. Then, once code has been generated, the development continues in a bottom-up fashion on the right side of the V, where the software artifacts are tested in reversed order as they are created. The V-model highlights the relationship testing has with the different phases of software lifecycle, visualizing how late-stage testing impacts early-stage development activities. For instance, if system testing highlights architectural problems, the development might suffer a significant setback. This reason lead to the adoption of new software processes, which stress on the importance of *test-driven development* [Beck, 2003]. Software testing is based on the concepts hereby defined [Ammann and Offutt, 2008].

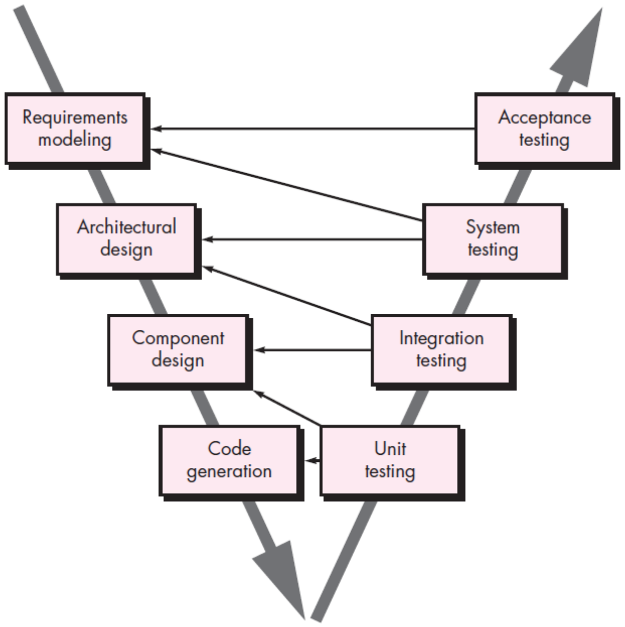


Figure 2.13. The V-Model for software development [Roger, 2005]

- **Fault (or Defect).** A fault is an anomaly in the system implementation, such as a wrong expression in the system source code.Faults are often caused by human errors, such as misinterpreting a requirement, forgetting some conditions, or mistyping an instruction. A system can have a fault that is not executed, and therefore has no effect on the system behavior. In this case, the fault is *dormant*. If the faulty instruction is executed, then the fault is *activated*.
- **Error (or Bug)** An error is a wrong internal state of an executing system, such as a program counter or an attribute with wrong values, caused by an activated fault. An error can have impact the observable behavior of a system. In this case, the error *propagates* to the outside.
- **Failure.** A failure is a deviation, caused by a propagated error, of the system behavior from the expected behavior. The system evaluation performed during software testing is mostly aimed at identifying failures in a system, so that the corresponding fault(s) can be corrected[5].
- **Test Case.** A test case is a set of data given as input to the SUT in order to observe the system behavior in a particular scenario. In general, a test case is a possible input to a system, such as a set of particular values that a system interface takes as a parameter. Given that the ultimate goal of testing is to identify defects, generating test cases that have high chance to reveal faulty behavior in the system is a critical task. The process of creating test cases for a system is known as *test case generation*.
- **Test Suite.** A test suite is a set of test cases. Since testing has to account time and budget constraints, it is not feasible to execute arbitrarily large test suites. In practice, one wants to find a balance between the size of the test suite, i.e., the time that it takes to execute all of its test cases, and the likelihood test cases have to reveal faults. This need is addressed by techniques known as *test suite optimization* or *test suite reduction*.
- **Test Case Specification.** A test case specification is a document containing the scenarios that test cases are meant to exercise. The test case specification is used to guide the test case generation process. Note that in Model-driven Engineering, both the system and the test case specification are represented by models (Section 2.3.1).
- **Test Oracle.** A test oracle is a map that associates to each test case in a test suite its expected behavior. Typical oracles consist of past versions of the same system, standards the system must conform to, or user expectations.
- **Test Framework (or Test Harness).** A test framework is a tool that supports (semi-)automation of the testing process, including the generation of test cases, their execution, the comparison with test oracles, and the generation of reports on the test executions.

It is well-known that testing, being based on the execution of a system, is a powerful technique to show the presence of defects, but can not show their absence [Dijkstra et al., 1970]. Indeed, the potential size of input space and the presence of unbounded loops within the system control flow renders exhaustive testing practically infeasible. This motivates the need to assess the quality of test suites, in order to reduce costs and gain confidence that the system has been properly tested. Evaluating the quality of test suites is mostly done by assessing the extent to which the system is thoroughly tested, and the capability of test cases to reveal faults. These two aspects are investigated trough *test coverage*

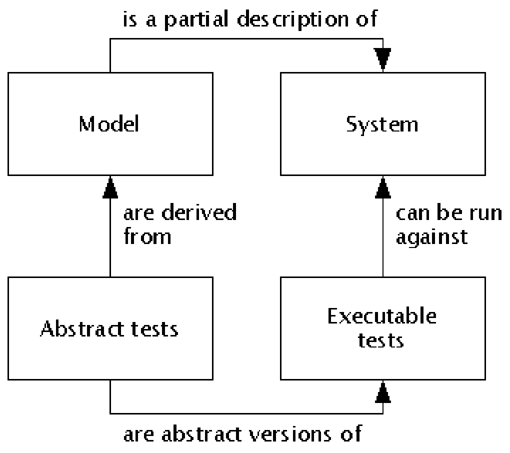
[5] Note that testing is aimed at detecting system failures, not at diagnosing their causes. Indeed, the process of identifying the faults that cause failures is referred to as *debugging*. Nevertheless, testing and debugging are often mixed up.

criteria and *mutation-based analysis*, respectively. Test coverage is a measure of the proportion of a system exercised, i.e., *covered*, by a test suite [Rapps and Weyuker, 1985]. This proportion can be measured with several criteria that reason over the system at different levels of abstractions, considering user requirements (*requirement-based* criteria), control flow graphs (*control-flow-based* criteria), state machines (*transition-based criteria*), internal variables usage (*data-flow-based criteria*), and partitions of input values (*boundary-based criteria*). For instance, transition-based criteria consider the system as a state machine, and measure the percentage of states or transitions visited when executing the test suite. Mutation analysis is a technique to measure the fault detection capability of a test suite [DeMillo et al., 1978]. The idea behind mutation analysis is to inject faults into a correct implementation of a system, thus creating faulty implementations called *mutants*. The test suite is then executed on each mutant, and the number of mutants that reveal faults, referred to as *killed* mutants, determines the quality of the test suite.

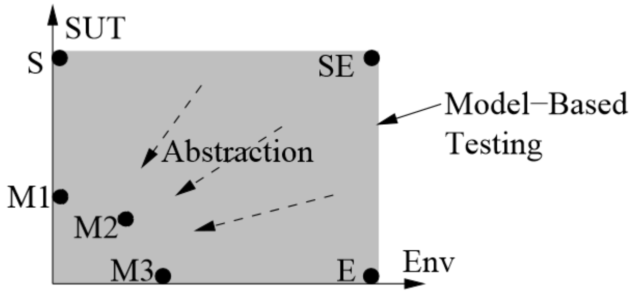
Testing not only affects the development costs of software, but also its quality [Deutsch and Willis, 1988]. For this reason, software testing has been adopting formal and structured approaches. Indeed, many techniques for software testing have been devised over the years. One of the most important classifications of testing strategies distinguishes *black-box* from *white-box* testing [Pressman and Jawadekar, 1987]. Black-box testing techniques assume no details on the system implementation, interacting exclusively with user interfaces. The SUT is then seen as a black box, whose behavior is only determined through the input-output relationships revealed during testing. Black-box testing is particularly useful when system details are not available, allowing for an objective perspective that avoids bias when generating test cases, due to knowing the fundamental aspects of the system. On the other hand, having no details on the parts of the system exercised by each test case renders achieving satisfactory testing coverage challenging. In white-box testing, the SUT is instead completely accessible. This allows a more effective generation of test cases, where coverage criteria can be taken into account. However, white box testing comes at the cost of requiring a careful investigation of the system artifacts to be more effective than black-box testing. Note that it is beyond the scope of this thesis to discuss a complete taxonomy of testing approaches. However, we briefly describe three most relevant areas for this thesis, namely Model-based Testing (Section 2.3.1), Performance Testing (Section 2.3.2), and Search-Based Software Testing (Section 2.3.3).

2.3.1 Model-based Testing (MBT)

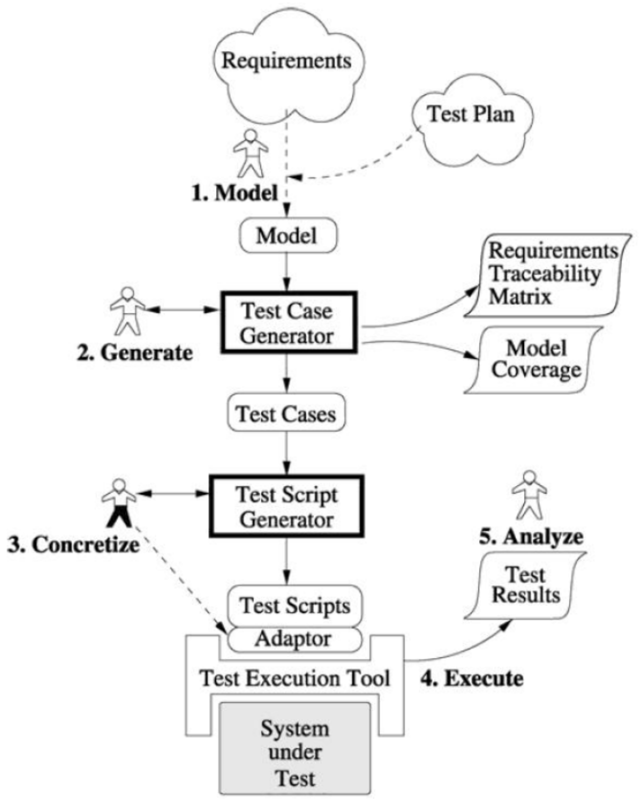
Model-driven Engineering (Section 2.2) is based on use of models as main artifacts during every phase of software development, including testing. This lead to the definition of Model-based Testing (MBT) as an approach for deriving test cases from system models (Figure 2.14), implying that the test case specification is also represented as a model. Even though there is no universal definition for MBT [Binder, 2000], Figure 2.14.1 shows one of the most common understandings. The main idea behind MBT is that the specification of a system behavior can not only be used to guide development, but also to derive test cases that exercise particular behaviors. Specifically, models can be used to derive *abstract* test cases representing test data and scenarios. These abstract test cases model *executable* test cases, which can be run on the system once implemented. One of the main advantages of MBT is that test cases are generated from system models, which in turn are derived from requirements. Indeed, linking the test cases to system requirements simplifies their readability, understandability, and maintainability [Utting et al., 2006].



(2.14.1) Relationships between system, models, and test cases in MBT



(2.14.2) Levels of abstraction in MBT [Utting et al., 2006]



(2.14.3) A typical MBT process [Utting and Legeard, 2010]

Figure 2.14. Overview of Model-based Testing: the system models are used to drive the generation of test data (*abstract test cases*), that characterizes *executable test cases*

Similar to MDE, models in MBT can be defined at different levels of abstraction. Figure 2.14.2 shows a graph where the x- and y-axes report the level of detail of the environment and system models, respectively. The models *S*, *E*, and *SE* represent the extreme cases, where the model formalizes all the details about the System, the Environment, or both. Such models are often too detailed to be managed, so in MBT these details are typically abstracted away as in *M*1, *M*2, and *M*3. This is also a common practice in MDE.

Figure 2.14.3 shows a typical MBT process, which consists of five main steps: (1) starting from a model of the system, (2) generate abstract test cases, (3) transform them into executable test cases which are (4) run in the system, and finally (5) analyze the results, possibly comparing them with test oracles [Utting and Legeard, 2010]. Another advantage of MBT is that the generation of abstract test cases and their transformation into executable test cases (*test cases* and *test scripts* in Figure 2.14.3, respectively) can be automated with relatively low effort [Utting and Legeard, 2010]. Usually, executable test cases are generated via model transformation of the corresponding abstract test cases. There exist several possible techniques for generating abstract test cases, mostly depending on *test selection criteria* and *generation technology* [Utting et al., 2006].

In practice, it is not possible to exhaustively test the set of behaviors represented by models of large systems. When generating test cases from a model, it is then necessary to define some criteria to chose the behaviors to test. In this way, the test selection criteria define a test suite. There exist seven main types of test selection criteria for MBT [Utting et al., 2006].

- **Requirement-based criteria** aim at providing coverage of the system requirements. To implement these criteria, requirements need to be traced to system models, so that each test case generated exercises one or more system aspect expressed in a requirement.
- **Specification-based criteria** are based on the test case specification. Even though it is in general independent from the system models, the test case specification is often expressed with formalisms such as Finite State Machines (FSM), constraints, and regular expressions [Utting et al., 2006]. These formalisms are often used in conjunction with UML profiles such as the UML Testing Profile (UTP) [OMG, 2013], in order to provide the adequate abstraction level to generate test cases representing the scenarios in the specification [Baker et al., 2008].
- **Structure-based criteria** select test cases based on the structure of the model, typically with control-flow-based, transition-based or state-based coverage criteria [El-Far and Whittaker, 2001].
- **Data-based criteria** are based on the decomposition of the input space into equivalence classes, as in boundary-based coverage criteria. In this way, that test cases can be selected to exercise one representative value from each class.
- **Mutation-based criteria** are based on the concept of mutation analysis. Even though mutation analysis has been defined as a strategy to evaluate the quality of test suites, its principles can also be applied to drive test case generation. This is mostly done by ensuring that the test cases generated kill a satisfactory number of mutants [Papadakis and Malevris, 2012].
- **Fault-based criteria** rely on the knowledge of typically occurring faults, which are often captured in the form of a fault model.
- **Probabilistic-based criteria** are based on stochastic models of the environment, and are mostly used when the usage patterns of the SUT are determined by such environment. Typical approaches profile the system usage with Markov chains or statistical models [Beyer et al., 2003].

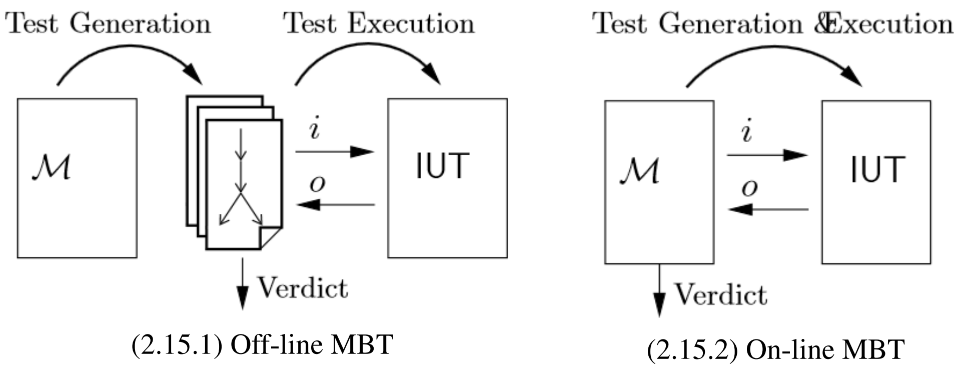
Abstract test cases generation can be classified under another dimension, orthogonal to selection criteria, concerning the technology that automates the generation of test cases. There exist four main technologies to automate test case generation in MBT [Utting et al., 2006].

- **Search algorithms** are generally used to generate test cases from behavioral models such as Finite State Machines. Indeed, state machines are graphs where to each node corresponds a state, and to each edge corresponds a transition between states. Commonly used selection criteria for state machines involve graph coverage, such as nodes, transitions, and cycles coverage. Test cases satisfying these criteria can be easily generated with search algorithms that explore the FSM graphs, and keep track of the paths yielding high coverage, which represent abstract test cases.
- **Model Checking (MC)** is a software verification technique that aims at verifying properties ex-

pressed in a model [Clarke et al., 1999]. Typically, a property is a condition that should never hold in the system at any given time. These properties are in turn formulated as reachability queries of a faulty state in a FSM, in such a way that MC verifies whether this faulty state is reachable or not from the initial state. If this is the case, MC returns a counterexample with the path leading to the faulty state, otherwise it terminates proving that the property never holds because the faulty state can never be reached. MC is mostly used in software engineering to compare a model with its specification, e.g., to check the absence of deadlocks in a FSM modeling task executions. However, MC can also be used for test case generation by formulating test case specifications as reachability properties in a state machine [Ammann et al., 1998]. For instance, a test case could be specified in a way that upon execution, the state S in the state machine M is reached at some point. In this case, MC can generate an abstract test case by computing a path in model M such that the state S is visited.

- **Theorem Proving** is another software verification technique that, similar to Model Checking, aims at verifying properties expressed in a model [Hoare, 1969]. However, while Model Checking casts these properties as reachability queries over a state machine, Theorem Proving verifies the same properties by casting them as logic formulas, and proving their satisfiability using deductive logic, such as Hoare Rules or Lambda Calculus [Halpern and Vardi, 1991]. However, Theorem Proving can be used for to generate abstract test cases in MBT by modeling the system behavior as a set of logical expressions (*predicates*). The model is then partitioned into equivalence classes over the valid semantic interpretations of the expressions. In this way, each equivalence class represents a system behavior, and is therefore an abstract test case [Brucker and Wolff, 2013].
- **Symbolic Execution (or Symbolic Evaluation)** is a technique aimed at determining what inputs cause given statements of a program code to execute [King, 1976]. Typically, an interpreter follows the program, assuming symbolic values for input variables. For each statement in the program, the interpreter assigns to variables expressions in terms of the symbolic values, based on the previous statements interpreted. Whenever the interpreter analyzes a conditional statement with n branches, it creates n logical constraints and associates each to the first statement the corresponding branch. When the program is fully analyzed, for each statement in the code the interpreter has created a constraint model consisting of constraints on the program variables. Then, in order to find concrete values for the input variables leading to the execution of a given statement, the corresponding constraint model is solved with a constraint solver (Section 2.4.1). In MBT, Symbolic Execution can be used as an alternative to Model Checking when proving reachability properties over executable models, e.g., models expressed with Executable UML (xtUML or xUML) [Mellor et al., 2002]. In this way, the concrete values found when solving a constraint model associated with a statement L represent an abstract test case that executes L.

Finally, there exist two fundamental strategies for generating and executing test cases in MBT, namely *off-line* and *on-line* approaches (Figure 2.15) [Hessel et al., 2008]. In the former, (Figure 2.15.1), test cases are executed in an Implementation Under Test (IUT) after the test suite is fully generated. In this way, the test cases execution process is straightforward, because it is decoupled from generation. In addition, the test suite can be optimized prior to execution, for instance by eliminating redundant test cases and by ensuring the satisfaction of some coverage criteria. On the other hand, in on-line approaches



(2.15.1) Off-line MBT (2.15.2) On-line MBT

Figure 2.15. Off-line and on-line approaches for MBT [Hessel et al., 2008]

test generation and execution happen one after the other in a feedback loop (Figure 2.15.2). In this way, the outcome of past test cases can possibly influence the generation of new ones. On-line testing may continue until some coverage or fault-detection criteria have been satisfied. This approach is mostly used for systems where testers can not inject some of the inputs, such as non-deterministic systems whose environment is hard to effectively simulate.

2.3.2 Performance and Stress Testing

Software testing has historically focused on functional aspects, and has mostly been intended as a mean to ensure that each system input corresponds to the expected output. However, the degradation in performance can have potentially severe consequences, even worse that unexpected system responses [Weyuker and Vokolos, 2000]. This is especially true in the context of safety-critical systems, where responding timely to external inputs is as important as processing them in the correct way. Therefore, many studies stated the importance of performance testing, especially during early development stages, when the system architecture is finalized [Denaro et al., 2004]. This aspect highlighted the need of methodologies flexible enough to combine performance testing with early design-time analysis [Woodside et al., 2007].

For practitioners, performance testing investigates whether or not a software system handles the expected user load by responding quickly enough [Barber, 2003]. Indeed, a common definition of performance testing involves the systematic evaluation of a System Under Test under realistic conditions, in order to check whether performance requirements are satisfied or not [Binder, 2000]. This definition entails the investigation of abstract concepts such as the *capacity* and *limits* of the system, which are defined in the performance requirements [Gao et al., 2003]. For this reason, performance test cases are designed starting from such requirements, which in turn can be expressed in different ways, depending on the system scope, domain, and objectives. In this thesis, we focus on the description of performance testing in the context of safety-critical Real-Time Embedded Systems, where the most important concern is ensuring a timely reaction to external triggers (Section 2.1).

Figure 2.16 depicts a typical performance testing process, which consists of five main steps [Gao et al., 2003].

1. **Selection of Performance Requirements.** The first step is to identify the concepts characterizing the performance of the tested system [Nixon, 2000]. In RTES, common performance requirements involve task deadlines, response time, and computational resources utilization, such as CPU, memory and network bandwidth. Performance requirements are then formalized in formal *metrics* that are measured during testing [Jain, 1991].
2. **Definition of the Workload (or Performance Evaluation Model).** The requirements selected are then used to drive the definition of the workload, which consists of the scenarios that the system has to be tested in. The workload contains all the basic information characterizing performance test cases. Indeed, at the lowest level of abstraction, each scenario corresponds to one test case.
3. **Definition of the Performance Test Plan.** Performance requirements, metrics and workload are documented in a performance test plan. The test plan also contains technical information related to test execution, such as hardware used, software versions, tools and test schedule.
4. **Generation of the Performance Test Report.** After test cases execution, the final step is to prepare a report that documents the results in order to analyze system performance. The resulting report includes the measured values of performance metrics, possibly with graphs displaying their evolution over time.

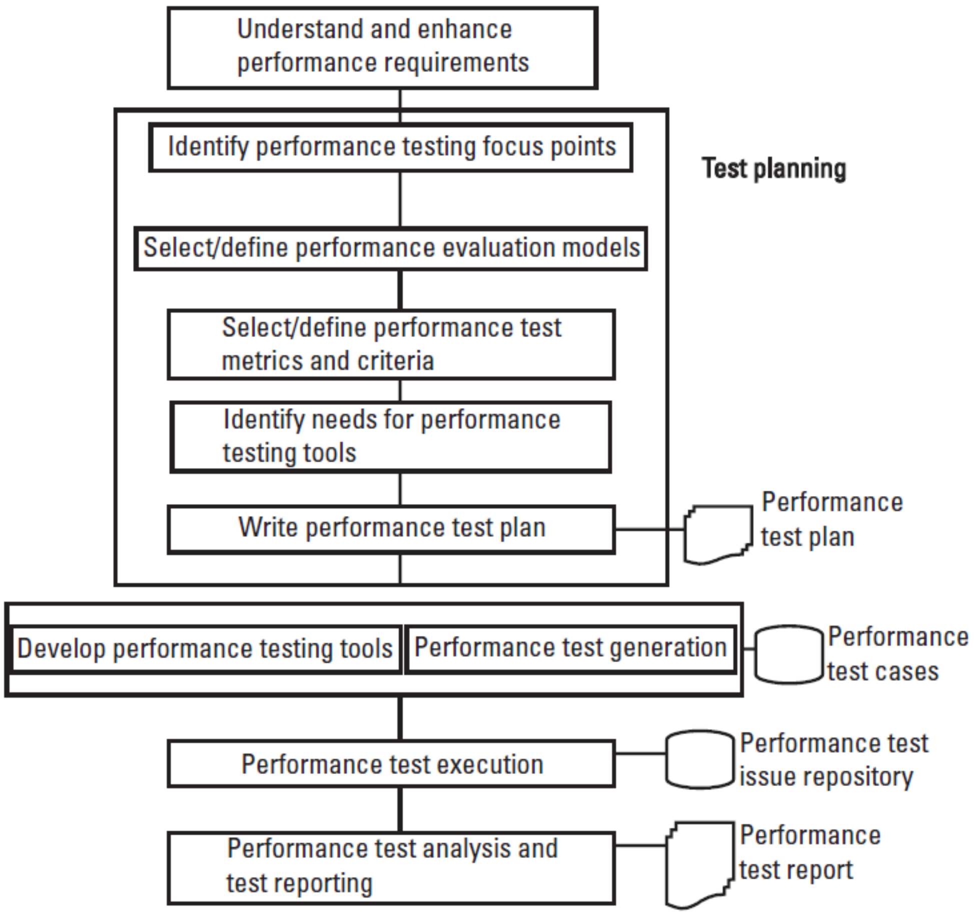

Understand and enhance performance requirements
Identify performance testing focus points
Test planning
Select/define performance evaluation models
Select/define performance test metrics and criteria
Identify needs for performance testing tools
Write performance test plan
Performance test plan
Develop performance testing tools
Performance test generation
Performance test cases
Performance test execution
Performance test issue repository
Performance test analysis and test reporting
Performance test report

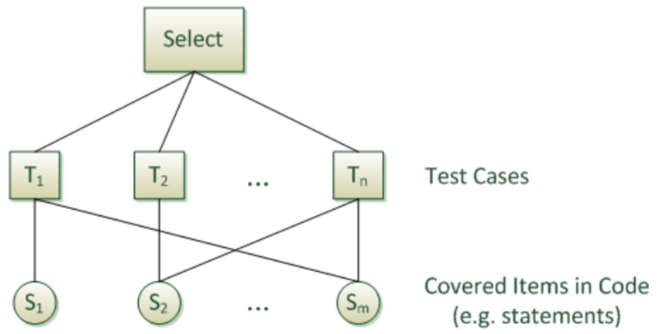
Figure 2.16. A typical performance testing process [Gao et al., 2003]

The performance testing process is thus centered on the definition of a workload that the system is exposed to. The workload is also called *operational profile*, as it can be seen as a mean to profile the system behavior [Musa, 1996]. In the domain of distributed systems, the workload is often defined through the use of *traffic models*, which stochastically predict the most likely user interactions with the system [Hong and Rappaport Stephen, 1986]. However, RTES interact with the external environment, which is intrinsically hard to predict prior to system execution. This renders the definition of RTES workloads a challenging task, as popular techniques such as *workload characterization* based on historical data or stochastic models can be rather ineffective. This is especially true in the context of safety-critical systems, where it is mandatory to test performance in worst-case scenarios, rather than only in the most common ones. Workloads are usually classified into *real* and *synthetic* workloads [Jain, 1991]. A real workload corresponds to a set of actual operating scenarios that occur in a given time frame. Real workloads are useful to investigate the system under realistic conditions, but can not be controlled in practice. Indeed, they are not repeatable, and can not guarantee a significant variety of operating conditions. Nonetheless, systems can always be tested under real workloads. On the other hand, synthetic workloads are simulations of real conditions that can be repeatedly applied to the system, and controlled by testers. Whenever workload characterization is possible, synthetic workloads are created from real workload models, which classify particular system-user or system-environment interaction patterns. Note that, in the context of RTES, using synthetic workloads requires the capability to interact with the system by simulating the external environment.

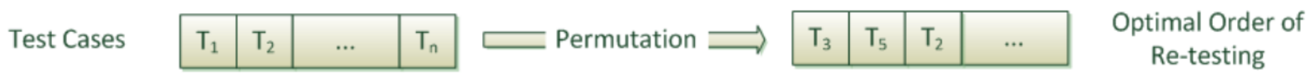
There exist several types of performance testing, each characterized by a specific workload that exercises given aspects of the SUT performance [Shannon et al., 2005]. In the context of safety-critical RTES, a major role in performance testing is played by *stress testing*, intended as testing a system under “unrealistically harsh inputs [. . .] with the intention of breaking it" [Beizer, 2002]. For this reason, stress test cases push the system “beyond its design limits" as they are “designed to cause a failure" [Binder, 2000]. Indeed, stress testing is the simulation of border-line cases that represent worst-case scenarios. Testing these scenarios is particularly important for safety-critical systems, where failures can not be tolerated as they may lead to catastrophic consequences for the system, its users and the environment. Therefore, stress testing workloads define worst-case scenarios, which in RTES are usually represented by particular sequences of external events triggering system tasks. These events are often signals coming from hardware sensors which carry *must-answer* data, such as alarms from fire, pressure or temperature sensors. In RTES, stress testing workloads are mostly characterized by the *timing patterns* of such events. Consider for instance a fire monitoring system that has to activate water sprinklers in case smoke is detected. When testing such a system, it is crucial to investigate whether the sprinklers are timely activated *whenever* there is a fire, i.e., *whatever the timing* of the fire detectors signals is. There could be (worst) cases where the alarm comes when the system does not have enough resources or is blocked in other operations, resulting in a failure to activating the sprinklers on time. Stress testing is ultimately aimed at investigating whether worst-case scenarios like these pose significant safety risks. However, as explained before, worst-case scenarios are hard to predict due to the environment unpredictability and the complex real-time interactions between components in large systems.

2.3.3 Search-based Software Testing (SBST)

Many software engineering activities can be very expensive in terms of time, effort, and resources. As a consequence, there have been many attempts in reducing the cost of these activities via automation [McClure, 1992]. Several methodologies have been proposed to automate software processes, for instance using data mining [Xie et al., 2009], code generation [Herrington, 2003], or automated reasoning [Benavides et al., 2005] techniques. One of the most popular approaches to automate software engineering activities is re-expressing them as *search problems*, i.e., problems consisting of (1) defining a set of objects of interest as problem *variables*, (2) defining a set of criteria to evaluate values (*solutions*) for these variables, and (3) finding, from the set of possible values (*search space*), solutions that fulfill the criteria at best. This approach is commonly known as Search Based Software Engineering (SBSE) [Harman and Jones, 2001], and has been successfully applied in several activities of software engineering, including requirements analysis [Greer and Ruhe, 2004], design [Clark and Jacob, 2001], maintenance [Antoniol et al., 2005] and project management [Alba and Francisco Chicano, 2007]. Out of all activities in software engineering, testing has been the first field where search-based techniques have been applied [Miller and Spooner, 1976]. Over the years, Search-Based Software Testing (SBST) has been successful in several areas of software testing, especially test case generation [McMinn, 2004], selection [Yoo and Harman, 2007], and prioritization [Li et al., 2007].



(2.17.1) Test case selection



(2.17.2) Test case prioritization

Figure 2.17. Two examples of software testing activities commonly solved with search-based techniques: test case selection and prioritization [Harman et al., 2012]

SBST is mostly centered around optimization problems, where the search aims at finding the best solutions with respect to some criteria. These solutions usually represent test data, rankings of test cases in a test suite, or sets of test cases fulfilling some requirement, such as optimal coverage. Figure 2.17 shows two examples of software testing activities commonly addressed in SBST. Figure 2.17.1 shows a mapping between test cases, and elements they cover, e.g., statements in code. The test case T_1 covers the statements S_1 and S_m, T_2 covers S_2 and T_n covers S_2 and S_m. The test case selection problem consists in finding the minimal set of test cases that achieves some coverage criteria. Note that, in this case, the search space grows exponentially in the size of the test suite. This is because, given a test suite T of n test cases, there exist 2^n subsets of T. Figure 2.17.2 shows an example of the test case prioritization problem, consisting in finding the optimal execution order of test cases with respect to criteria such as coverage or fault detection rate. Even in this case the search space grows exponentially in the size of the test suite: given a set of n test cases, there exist $n!$ permutations of test cases that define a sequence. These examples show that the search space is often too large to be exhaustively explored within a practically convenient time. For this reason, SBST makes a extensive use of search algorithms, namely *metaheuristics*, which aim at finding solutions by evaluating only a fraction of the search space [Harman, 2007]. We describe metaheuristics in Section 2.4.2.

2.4 Mathematical Optimization

Mathematical Optimization (or Mathematical Programming) is the discipline describing methods for solving *optimization problems*, i.e., problems that consist in finding the best (*optimal*) element(s), with respect to given criteria, from a set of alternatives. This best element is referred to as *global optimal solution* and it yields the *global optimum* value for the criteria. When such element is found, the corresponding problem is said to have been *solved to optimality* [Polak, 1997]. The optimization criteria are often expressed as *objective functions* whose codomain is a partially ordered set. In this way, the goal of an optimization problem is to find either the minimum or the maximum value of the function, and the values for the function variables that yield these minimum and maximum. Therefore, depending on their goal, optimization problems are referred to as either *minimization* or *maximization* problems. In general, an optimization problem can also specify that the optimum must present specific characteristics other than minimizing or maximizing the objective function. Based on the concepts above, we provide the following formalization of minimization and maximization problems [Snyman, 2005]:

Minimum of a function. *Let $f : X \to Y$ be a function whose codomain Y is a set with a partial order $\leq$, and let $X' \subseteq X$ be a subset of X. The minimum of f restricted to X' is denoted by $\min_{x \in X'} f(x)$, and defined by the following property.*

$$f(x^*) = \min_{x \in X'} f(x) \ \leftrightarrow\ \forall x' \in X' \cdot f(x^*) \leq f(x')$$

Argument of the minimum of a function. *Let $f : X \to Y$ be a function whose codomain Y is a set with a partial order $\leq$, and let $X' \subseteq X$ be a subset of X. The argument of the minimum of f restricted to X' is denoted by $\arg\min_{x \in X'} f(x)$, and defined by the following property.*

$$x^* = \arg\min_{x \in X'} f(x) \ \leftrightarrow\ \forall x' \in X' \cdot f(x^*) \leq f(x')$$

Note that, in general, a function f can have more than one minimum, and more than one argument of the minimum. Also note that, by definition, $f\Big(\arg\min_{x \in X'} f(x)\Big) = \min_{x \in X'} f(x)$.

Minimization problem. *Let $f : X \to Y$ be a function whose codomain Y is a partially ordered set, and let $X' \subseteq X$ be a subset of X. A (single-objective) minimization problem over f restricted to X' is a problem consisting in finding the minimum, and the argument of the minimum of f restricted to X'.*

Note that, in this thesis, we do not consider multi-objective optimization problems.

Maximum of a function. *Let $f : X \to Y$ be a function whose codomain Y is a set with a partial order $\leq$, and let $X' \subseteq X$ be a subset of X. The minimum of f restricted to X' is denoted by $\max_{x \in X'} f(x)$, and defined by the following property.*

$$f(x^*) = \max_{x \in X'} f(x) \leftrightarrow \forall x' \in X' \cdot f(x') \leq f(x^*)$$

Argument of the maximum of a function. *Let $f : X \to Y$ be a function whose codomain Y is a set with a partial order $\leq$, and let $X' \subseteq X$ be a subset of X. The argument of the maximum of f restricted to X' is denoted by $\arg\max_{x \in X'} f(x)$, and defined by the following property.*

$$x^* = \arg\max_{x \in X'} f(x) \leftrightarrow \forall x' \in X' \cdot f(x') \leq f(x^*)$$

Note that, in general, a function f can have more than one maximum, and more than one argument of the maximum. Also note that, by definition, $f\Big(\arg\max_{x \in X'} f(x)\Big) = \max_{x \in X'} f(x)$.

Single-objective Maximization problem. *Let $f : X \to Y$ be a function whose codomain Y is a partially ordered set, and let $X' \subseteq X$ be a subset of X. A (single-objective) maximization problem over f restricted to X' is a problem consisting in finding the maximum, and the argument of the maximum of f restricted to X'.*

Most practical optimization problems can be described with the formalizations above. Specifically, f is referred to as objective function, while max and arg max represent the global optimum and the global optimal solution, respectively. In practice, the key elements in these definitions, such as the function f or the subset X', often have specific characteristics that can be exploited to solve the problem. Therefore, Mathematical Optimization has different subfields that focus on solving particular classes of optimization problems. For instance, Combinatorial Optimization is aimed at solving optimization problems where the domain X of f is a finite set [Nemhauser and Wolsey, 1988], while Stochastic Programming focuses on problems where f depends on random variables [Birge and Louveaux, 2011]. In this thesis, we describe the two classes of optimization techniques that have mostly been applied to Software Engineering problems, namely Constrained Optimization (CO) (Section 2.4.1), and Metaheuristics (Section 2.4.2).

2.4.1 Constrained Optimization (CO) and Constraint Programming (CP)

Constrained (or Constraint) Optimization (CO) is a field in Mathematical Optimization that focuses on problems where the variables of the objective function are subject to logical relations named *constraints* [Gill et al., 1981]. Problems in CO are often referred to as Constraint Optimization Problems

(COP). Consistent to the definitions in Section 2.4, in COP the subset $X' \subseteq X$ of the objective function domain can be expressed as a set of constraints, usually in form of equalities or inequalities. Constraints enjoy a set of properties that simplify their adoption to model real-world problems [Lloyd, 1994]. For instance, constraints specify partial information on the variable values: usually, a single constraint does not uniquely specify the values for the problem variables, and has to be considered in conjunction with other constraints. However, constraints are commutative, as the order in which they are considered does not affect the set of values they describe. Constraints are declarative, as they only define relationships among variables without specifying computational procedures. Finally, constraints can be combined to infer other constraints. Consider for instance the variables x, y, and z, and the constraints $c_1 : x \leq y$, and $c_2 : y \leq z$. In this case, c_1 and c_2 can be used to infer the constraint $c_3 : x \leq z$.

In general, a solution of a COP has two key features, i.e., (1) satisfies all the constraints, and (2) optimizes the objective function. However, several practical problems only consist in finding solutions that satisfy a set of constraints, because there is no relevant function to optimize. These problems are commonly known as Constraint Satisfaction Problems (CSP). Even though CSP do not traditionally belong to the field of Mathematical Optimization as they are not optimization problems, they can be seen as COP where the objective function is constant [Apt, 2003]. Indeed, these two classes of problems are often treated together, because the techniques used to solve them all reason over constraints[6]. Specifically, both CSP and COP are solved through the means of Constraint Programming (CP). CP is a programming paradigm that expresses relationships among variables as a conjunction of logical constraints [Apt, 2003]. Note that, as explained before, constraints do not specify machine instructions to execute, but rather properties that characterize the values of variables[7]. For this reason, CP is a declarative paradigm, as are Logic Programming and pure Functional Languages. Since constraints do specify a way to compute values that satisfy them, COP and CSP are solved in CP through *constraint solvers*, which implement resolution algorithms based on different strategies. In general, these resolution strategies are based upon problem properties such as convexity or linearity. There exists a number of free and commercial constraint solvers, which are able to solve several types of COP and CSP: notable examples include ECLiPSe[8], Gecode[9], SICStus[10], and the IBM ILOG CPLEX suite[11]. These solvers take as input a CSP or COP, whose constants, variables, constraints and objective functions are specified in a *constraint model*. Constraint models are usually implemented in mathematical languages, which offer primitives and constructs for the definition of mathematical and programming objects, such as statements, variables, functions, lists, iterators and conditional expressions. Notable examples of such languages are A Mathematical Programming Language (AMPL) [Fourer et al., 1987], MiniZinc [Nethercote et al., 2007], and the Optimization Programming Language (OPL) [Van Hentenryck, 1999]. In the rest of this section, we formalize CSP

[6] Note that, given a COP P and a candidate optimal solution x^* which yields the objective value $f^* = f(x^*)$, it is possible to verify whether x^* is the global optimum by solving a CSP P'. In particular, P' has the same constraints of P, plus the additional constraint $f(x) > f^*$.

[7] Note that, opposite to constraints, primitives in imperative programming languages also imply the *computation* of the variables values.

[8] `http://eclipseclp.org/`

[9] `http://www.gecode.org/`

[10] `http://sicstus.sics.se/`

[11] `http://www.ibm.com/software/commerce/optimization/cplex-optimizer/`

and COP, and we introduce the major techniques used to solve them. Note that, as it often happens in the CP literature, we first introduce CSP in Section 2.4.1.1, and then COP in Section 2.4.1.2 as an extension of CSP.

2.4.1.1 Constraint Satisfaction Problems (CSP)

We formalize Constraint Satisfaction Problems (CSP) in the following way [Russell et al., 1995]:

Constraint Satisfaction Problems. *A* Constraint Satisfaction Problem $P = (X, D, C)$ *is a triple where:*

- $X = \{x_1, x_2, \ldots x_n\}$ *is a finite set of n* variables.
- $D = \{D_1, D_2, \ldots, D_n\}$ *is a finite set of n* domains*, where for each i, $D_i \in D$ is the domain of $x_i \in X$. Let $\phi : X \to D$ be the function that associates each variable to its domain, i.e., $\forall x_i \in X \cdot \phi(x_i) = D_i$.*
- $C = \{c_1, c_2, \ldots, c_m\}$ *is a finite set of m* constraints. *Each constraint $c = (X_c, R_c)$ is a pair where:*
  - $X_c \subseteq X$ *is a subset of variables, called the* scope *of the constraint.*
  - $R_c \subseteq \prod_{x \in X_c} \phi(x)$ *is a relation defined on the domains of variables in X_c.*

Given a variable $x_i \in X$, each element $d \in D_i$ is said to be a *value* for x_i. The *arity* of a constraint is the number of variables in its scope. A CSP P is said to be *binary* if all its constraints have arity one or two.

Variable assignment. *A* variable assignment *(or* assignment*)* $\theta : X \to \phi(X)$ *is a function that maps a variable $x \in X$ to one value in its domain $\phi(x)$, i.e., $\forall x \in X \cdot \theta(x) \in \phi(x)$.*

An assignment θ is said to be *complete* or *total* if it is a total function, i.e., if it assigns a value for each variable in X. An assignment which is not complete is said to be *partial*. A variable $x \in X$ is said to be *instantiated* in θ iff $\theta(x)$ is defined. Variables which are not instantiated in θ are said to be *unassigned* in θ. Note that, by definition, every variable in X is assigned in a complete assignment.

Satisfied constraint. *A constraint $c = (X_c, R_c)$ is said to be* satisfied *in an assignment θ, and is denoted by $c \models \theta$, iff the tuple of values assigned by θ to variables in X_c belongs to the relation R_c, i.e., iff $\Big(\theta(x) \mid x \in X_c\Big) \in R_c$.*

A constraint which is not satisfied is said to be *unsatisfied* or *violated*.

Consistent assignment. *An assignment θ is said to be* consistent *iff every constraint $c = (X_c, R_c)$ whose variables in X_c are assigned by θ is satisfied, i.e., iff $\forall\Big(c \in C \mid \forall x \in X_c \cdot \theta(x) \in \phi(x)\Big) \cdot c \models \theta$.*

Feasible Solution of a Constraint Satisfaction Problem. *A* (feasible) solution *of a CSP P is a complete consistent assignment.*

Note that a complete assignment is an element of the set $S = \prod_{x \in X} \phi(x)$, which is the Cartesian product of the domains in D. Since S is the set of all the complete assignments of variables in X, it is a superset of all the solutions of a CSP P. For this reason, S is said to be the *solution space* of P. In general, the solution of a CSP can be seen as a search problem (Section 2.3.3) over S whose criteria is the completeness and consistency of the assignments. Also note that a partial consistent assignment is said to be a *partial solution*.

A well-known example of a CSP is the *n-queens problem*, which consists in placing n queens on a $n \times n$ chessboard in such a way that queens do not attack each other [Bruen and Dixon, 1975]. Two queens are said to attack each another if they are on the same row, column or diagonal of the chessboard. This problem can be modeled as CSP where:

- $X = \{x_1, x_2, \dots x_n\}$ is the set of variables, where x_i represents the column of the queen in the i^{th} row.
- $D = \{D_1, D_2, \dots, D_n\}$ is a the set of variables domains where for each i, $D_i = \{1, 2, \dots n\}$. Note that the assignment $\theta(x_i) = j$ means that the queen on the i^{th} row is placed in the j^{th} column of the chessboard.
- C is the set of constraints that define relations such that $\forall x, j \in [1, n] \cdot x_i \neq x_j \wedge \mid x_i - x_j \mid \neq \mid i - j \mid$.

A solution of the n-queens problem for $n = 8$ is shown in Figure 2.18.

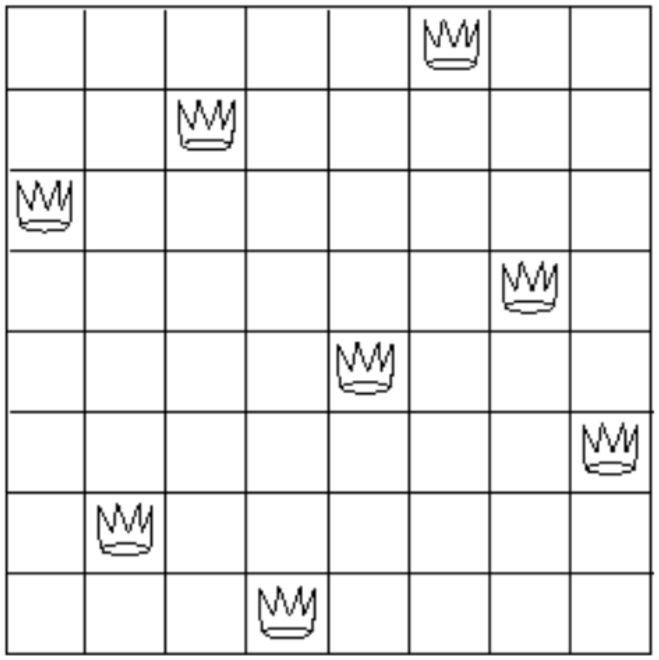


Figure 2.18. A solution for the n-queens problem in the case $n = 8$ [Abelson and Sussman, 1983].

In the domain of Software Engineering, several problems have been modeled as CSP, including project staffing [Barreto et al., 2008], product-lines feature modeling [Benavides et al., 2005], formal verification [Cabot et al., 2008], and test data generation [Gotlieb et al., 1998].

There exist several techniques to solve CSP, most of which are based upon (systematic) *tree search*. The idea behind tree search is to model the search space as a tree where each node represents the assignment of a value to a single variable. The children of each node represent mutually exclusive choices on the values to assign to each variable, effectively partitioning the solution space into disjoint sub-spaces.

In this way, each root-leaf path in the tree corresponds to a complete variable assignment. However, the tree exponentially grows in the number of variables and the size of their domains. This means that generating all the possible complete variable assignments and checking their consistency is infeasible for large problems. To address this problem, there exist tree search techniques that use *(chronological) backtracking* [Van Hentenryck, 1989]. In these techniques, the search tree is constructed and explored in a depth-first process, which starts from a node with all the variables unassigned, i.e, with an empty partial solution. At each iteration, the backtracking algorithm extends a partial solution by assigning a value to an unassigned variable. This step is called *labeling*. If the new partial solution violates any of the constraints of the problem, a *fail* is said to be detected. In case of fail, the most recent assignment is invalidated in a step *backtrack*. Then, the search continues iterating by assigning a value to the first unassigned variable. The algorithm stops when a solution is found, i.e., when all variables are assigned in a way that no constraint is violated, or when no more labeling or backtracking is possible because no solution exist. In general, the efficiency of the search process is influenced by the order in which the variables and values are tried for assignments. The strategies to choose what variable and what value to assign at each iteration are known under the name of *variable and value ordering heuristics*. In general, the values and variable order can be chosen either before the algorithm starts (*static ordering*), or at runtime depending on the current node of the tree (*dynamic ordering*) [Gent et al., 1996]. For instance, *first-fail* is one of the most common heuristics, which consists in ordering the variables in such a way that the tree levels have an increasing order of children [Haralick and Elliott, 1980]. This strategy is based on the principle that, the earlier a fail is detected, the larger is the sub-tree that is proved to have no solutions, and that hence does not to be visited. For many problems of practical interest, proper ordering heuristics can significantly speed up the search process. However, if heuristics choose a wrong assignment early in the tree, the search is likely to take too much time to backtrack and invalidate that early choice. This is because the efficiency of backtracking strongly depends on whether heuristics are able to choose the right branch early in the tree. A backtracking strategy called Limited Discrepancy Search (LDS) tries to mitigate this problem under the assumption that, most of the time, ordering heuristics chose the wrong assignments for variables only a small amount of time [Harvey and Ginsberg, 1995]. LDS remembers each branch of a path p that ends with fail. Instead of the usual backtracking step, LDS tries the set of paths that differ from p by a single branch. If all of these fail, then LDS tries the paths that differ from p by two branches, and so on. However, backtracking suffers in general from two major drawbacks: (1) *late fail detection*, due to fails not being detected before the corresponding branch in the tree is taken for exploration. This can potentially lead the search to spend time on sub-trees that have no solution. (2) *redundancy*, due to conflicting values of variables not being remembered. This can potentially lead to repeated fails due to the same reason. For this reason, there exist several strategies aimed at mitigating these two drawbacks. Late fail detection is usually addressed through *look-ahead* strategies, which aim at predicting whether or not a tree branch leads only to fails (*dead-end*) [Apt, 1999]. This is usually done through Constraint Propagation algorithms, which eliminate from the solution space assignments inconsistent with some constraints [Haralick and Elliott, 1980]. Constraint Propagation considers the CSP constraints in increasing order of arity, and progressively eliminates (*filters*) from the variables domain the values that violate such constraints. This domain reduction is referred to as *domain filtering*. Consider for instance a CSP where the variable x has domain $[1,5]$, and is subject to the unary constraint c stating that $x \leq 3$. Constraint Propagation starts the filtering process by reducing the domain of x to the interval $[1,3]$, because assigning 4 or 5 to x leads to a violation of c. Consider also the case where the same CSP has a variable y with domain $[0,7]$, which is subject to the binary constraint $y \geq x+2$. Since x is at least 1, y has to be at least 3, and therefore the Constraint Propagation algorithm filters the domain of y reducing it to the interval $[3,7]$. Constraint Propagation repeatedly applies domain filtering until no more deduction is possible. There exist several strategies to perform Constraint Propagation and domain filtering. For instance, *forward checking* is a look-ahead strategy that performs Constraint Propagation at each branch of the tree [Haralick and Elliott, 1980]. There exists also another class of techniques, namely *look-back* strategies, which aim at addressing the backtracking redundancy by either deciding how far to backtrack at each step, or by remembering the causes of past fails [Bayardo Jr and Schrag, 1997]. For instance, *backjumping* detects conflicting variables of a fail, and backtrack directly to the assignment of those variables, instead of the most recently assigned variable [Dechter and Frost, 2002]. On the other hand, techniques such as *backchecking* and *backmarking* record compatible and incompatible sets of assignments for variables. In this way, the search algorithm does not spend effort into checking whether an assignment occurred in the past leads to a fail or not, and does not consider for future branches assignments which are already known to lead to fail.

2.4.1.2 Constraint Optimization Problems (COP)

A Constraint Optimization Problem (COP) can be considered as a Constraint Satisfaction Problem extended by an *objective (or cost)* function that evaluates the quality of each solution. Therefore, we formalize COP in the following way [Russell et al., 1995]:

Constraint Optimization Problem (COP). *A Constraint Optimization Problem (COP) P is a couple (P',F) where:*

- *$P' = (X,D,C)$ is a CSP.*
- *$F : \big(X \to \phi(X)\big) \to V$ is an* objective (or cost) function *that associates a variable assignment of P' to a set V with a partial order $\leq$. F is defined only for complete consistent variable assignments (solutions).*

Note that, when referring to variables, domains or constraints of a COP, we intend the ones of the associated CSP. Also note that, for most practical problems, the partially ordered set V is a numerical set such as $\mathbb{N}$, $\mathbb{Z}$, $\mathbb{Q}$ or $\mathbb{R}$.

Preferred solution. *A solution θ_1 is said to be* preferred *to a solution θ_2, iff the value of the objective function applied to θ_1 is less than the value of the objective function applied to θ_2, i.e., iff $F(\theta_1) \leq F(\theta_2)$.*

Optimal solution. *A solution θ is said to be* optimal *iff no preferred solution θ' to θ exists, i.e., iff $\forall \theta' \in \{X \to \phi(X)\} \cdot F(\theta) \leq F(\theta')$.*

Note that this formalization is consistent with the generic definitions given at the beginning of this Section. Specifically, the objective function F of a COP can be seen as a generic function $f : A \to B$ that maps an assignment in A to a value in a partially ordered set B. Specifically, f is defined only for the complete consistent assignments (solutions) in $A' \subseteq A$. In this way, the argument of the minimum of f

restricted to A' is exactly the solution $s \in A'$ such that $f(s)$ is the minimum of f[12].

A well-known example of COP is the *job-shop scheduling problem*, which consists in assigning a set of jobs to processing machines [Coffman and Bruno, 1976]. Each job is a sequence of tasks, each completed in a given processing time. Tasks must be performed in a specific order, and on a specific machine. Therefore, a solution to the problem is a schedule of job sequences on machines, such that no machine is processing two tasks at once. In general, machines consume resource while operating, and one wants to minimize the total time where the set of machines is active. Therefore, the optimal solution to a job-shop scheduling problem is a schedule which minimizes the jobs *makespan*, i.e., the total elapsed time between the beginning of the first task, and the completion of the last task. Among several application fields, COP have indeed been used for scheduling analysis, especially in the domain of manufacturing systems [Baptiste et al., 2001].

The techniques to solve COP are mostly extensions of the tree search algorithms to solve CSP. Specifically, *Constructive algorithms* gradually extend a partial solution to a complete one. The basic constructive algorithm is *branch-and-bound*, which iteratively searches for solutions by applying backtracking and constraint propagation to the search tree [Lawler and Wood, 1966]. Opposite to algorithms for CSP, branch-and-bound does not stop as soon as a feasible solution is found, but keeps track of the best solution found (*incumbent*), and its cost (objective function *upper bound*). At each iteration, the algorithm searches for a solution with a lower cost than the upper bound. To do so, it evaluates the best value that the partial solutions can yield once all of its variables are assigned (objective function *lower bound*). Each time a value is assigned to a variable in the partial solution, the lower bound of that assignment is computed. If the lower bound is greater than the upper bound, the subtree under the current partial assignment can not contain a solution with a better cost, and is *pruned* from the tree.

Most approaches for COP are *complete*, in the sense that they return the optimal solution upon termination. However, for large problems, complete approaches can take long time to terminate. For this reason, *incomplete* techniques have been devised to solve COP, and optimization problems in general. Such techniques are discussed in Section 2.4.2.

2.4.2 Metaheuristics

In the field of Mathematical Optimization, there exist some problems whose global optimum is too hard to find within reasonable time. This mostly happens when the objective function is hard to express through equations, and no analytic or numerical approximation technique can be used to solve the problem. In such cases, the optimal solutions often have unknown characteristics, and the set of all possible solutions is too large to be enumerated. However, most of the time, generating an arbitrary solution to the problem requires significantly lower effort than finding the optimum. In such cases, the problem is often cast as a search problem. Recall from Section 2.3.3 that a search problem is a problem that consists of three main

[12] Traditionally, COP are defined as minimization problems. This is because a maximization problem of a function f with values in a partially ordered set B can be seen as a minimization problem of the same function where the partial order of B is inversed. For most practical problems, the partial order is a numerical set. In this case, maximizing f is indeed equivalent to minimizing $-f$. When not specified, in this thesis we assume that a COP models a minimization problem.

characteristics: (1) the definition of problem *variables*, (2) the definition of criteria to evaluate values (*solutions*) for these variables, and (3) the process of finding, from the set of possible values (*search space*), solutions that fulfill the criteria at best.

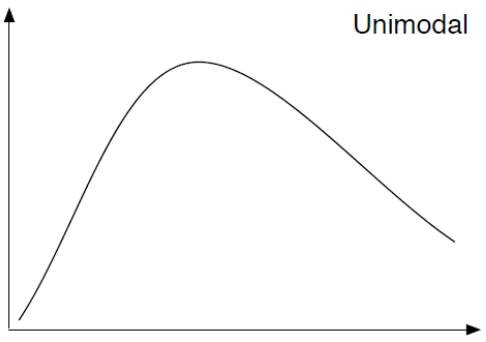
The field of Stochastic Optimization studies *randomized* algorithms and techniques which attempt at finding optimal solutions to these hard search problems. Specifically, *metaheuristics* is a term often used to describe the most general class of Stochastic Optimization algorithms[13] [Luke, 2009]. These algorithms can be used whenever it is possible to generate solutions and evaluate their quality. Opposed to analytical gradient-based methods [Snyman, 2005], metaheuristics do not require the search criteria to be expressed as functions, and therefore they are often referred to as *black-box* techniques. However, the search criteria are often referred to as *objective function(s)* to maximize or minimize, even though they are not usually expressed as mathematical objects. Metaheuristics are used to solve problems in many domains, including Software Engineering. Indeed, metaheuristics are extensively used in the area Search-Based Software Testing for test case generation, selection, and prioritization (Section 2.3.3).

2.4.2.1 Random Search and Hill-Climbing

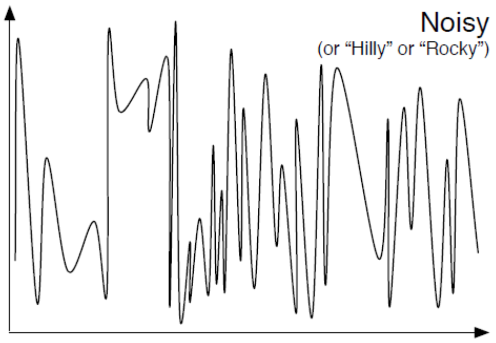
In general, all metaheuristics can be described in terms of five steps [Luke, 2009]: (1 – *initialize*) provide an initial set of solutions, (2 – *assess*) evaluate the quality of the solutions, (3 – *tweak*) create a new set of solutions by randomly modifying the existing ones, (4 – *select*) define a new set of solutions by choosing a mix of old and new solutions to keep in memory, (5 – *iterate*) repeat steps 2-4 until given termination criteria are reached. The solutions in steps 1-4, which the algorithm uses to drive the search towards the optimum, are typically referred to as *candidate solutions* of the problem at a given iteration. Given this description in five steps, metaheuristics differ from each other based on the logic behind steps 3 and 4. The most naive search algorithm is Random Search, where solutions are randomly generated and evaluated against the search criteria [Hamlet, 1994]. The generation process can continue until the time or resource budget expires, and usually returns only the best solutions found. For instance, Random Testing has been used in the context of Software Engineering for long time, proving to be effective in several case studies [Duran and Ntafos, 1984]. However, most search algorithms exploit specific properties of the solutions in an attempt to perform better than Random Search in terms of quality of solutions found, and time needed to find such solutions. The simplest algorithm that implements a basic reasoning over the solutions found is Hill-Climbing [Blum and Roli, 2003]. This algorithm first randomly generates a solution, and then creates a new version by making a small random modification. Then, it keeps the best version with respect to the search criteria, and continues iterating by making new modifications to the last kept solution. Hill-Climbing attempts at exploiting the supposition that similar solutions have similar quality with respect to the search criteria. In this way, small modifications generally result in small changes in quality, and keeping the best version of two solutions allows to *climb the hill* of quality, up to reaching a *plateau* where these small modifications do not increase quality anymore.

[13] Note that there is no universal agreement on a definition for metaheuristics. In general, Stochastic Optimization techniques such as Simulated Annealing, Evolutionary Algorithms, or Swarm Intelligence are traditionally seen as metaheuristics, while others such as Markov Chain Monte Carlo or Gibbs Sampling are not. To avoid confusion, in this thesis we do not distinguish between the terms of *metaheuristic* and *(randomized) search algorithm*, even though in the literature this is not always the case.

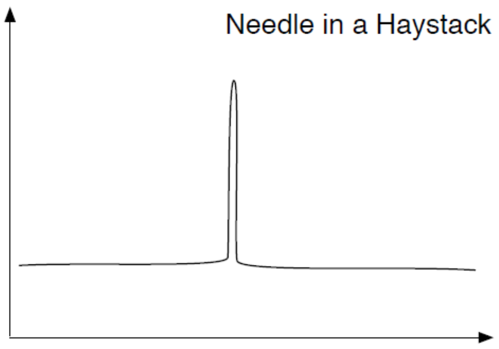
Note that Random Search and Hill-Climbing are based upon two fundamentally different strategies to find optimal solutions. On the one hand, Random Search continuously generates solutions unrelated to each other, thus *exploring* the search space in an attempt to find the optimum. On the other hand, Hill-Climbing starts from one solution and *exploits* it by incrementally improving it with small modifications. Random Search fundamentally implements a *Global Search* strategy, by visiting different regions of the search space. Hill-Climbing instead implements a *Local Search* strategy, where small moves are made in the most promising directions of the search space. Global, explorative algorithms such as Random Search and local, exploitative algorithms such as Hill-Climbing perform very differently based on the shape of the function to optimize.



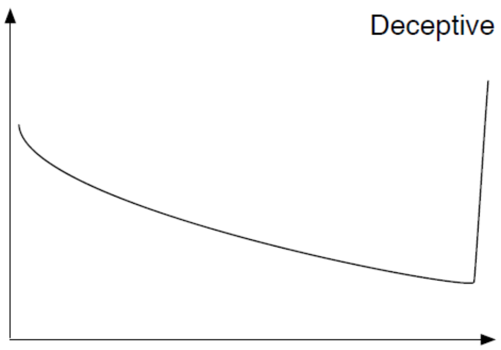
(2.19.1) Unimodal function



(2.19.2) Noisy function



(2.19.3) Needle-in-a-Haystack type of function



(2.19.4) Deceptive function

Figure 2.19. Four examples of quality functions where Random Search and Hill-Climbing tend to perform very differently [Luke, 2009]

Consider for instance Figure 2.19, where each graph depicts an objective function to maximize. The x-axes report the solutions in the search space, while the y-axes report the value of the objective function. Hill-Climbing performs very well in cases such as in Figure 2.19.1, where there is a strong relationship between the distance along the x-axis of two candidate solutions, and their quality. In this scenario, Random Search is very unlikely to reach the global optimum. However, when there is no relationship between the distance of two solutions and their quality (Figure 2.19.2), Hill-Climbing is likely to converge to a local optimum, possibly with a similar objective value as Random Search. In general, Hill-Climbing is effective when the objective function has an *informative* gradient, which leads the search towards high quality solutions. In the unimodal and noisy functions, there is such gradient, and Hill-Climbing is guaranteed to find the best solution within the neighborhood of the initial solution. Consider now the function in Figure 2.19.3: in this case, there is no gradient to guide Hill-Climbing towards the optimum. There are also cases, such as Figure 2.19.4, where the exploitation strategy of Hill-Climbing is counterproductive, since the gradient is likely to lead the search away from the optimum. In these last two cases, a global search approach is more likely to perform better than local search. For vast majority of optimization problems where metaheuristics are applied, the shape of the objective function is not known, and therefore it is not possible to predict whether an explorative or exploitative behavior is preferable. For this reason, metaheuristics essentially combine the principles of Random Search (global explorative search), and Hill-Climbing (local exploitative search) [Glover and Kochenberger, 2003].

2.4.2.2 Genetic Algorithms (GA)

Many metaheuristics have been defined over the years, most of which have been successfully applied to solve problems in Software Engineering [Harman, 2007]. However, it is beyond the scope of this thesis to provide a thoughtful discussion on the different kinds of randomized search algorithms. In the context of Search-Based Software Testing, the literature [Ali et al., 2010] reports successful results especially when using a class of metaheuristics known as Genetic Algorithms (GA) [Goldberg, 2006]. Although there is no universally accepted definition, one can identify four elements that most methods referred to as GA have in common: (1) *populations* of individuals, (2) *selection* according to fitness, (3) *crossover* to produce new offspring, and (4) random *mutation* of new offspring [Mitchell, 1998]. Each individual is referred to as *chromosome* or *genotype*, and represents a candidate solution for a given problem. Chromosomes consist of a set of *genes*, where each gene encodes a value in the solution. The number of genes in a chromosome, is often referred to as the chromosome *length*. A typical GA starts by randomly generating a population of chromosomes, and evaluating their fitness by calculating the value of a *fitness function*. Then, the algorithm iterates through a series of generations consisting of three main steps. (1) First, a pair of chromosomes is randomly selected with increasing probability according to fitness. (2) Then, the pair is crossed over to form two offspring, whose genes are then randomly mutated. (3) Finally, the offspring replaces two chromosomes the population, chosen with decreasing probability according to fitness. Each of these three steps is performed by a specific *operator*, which implements the logic of selecting, crossing-over, and mutating chromosomes. Similar to what happens in nature, during a series of generations the fittest chromosomes tend to survive in the population, while the unfit are discarded. The main assumption behind GA is that high quality parents produce a high quality offspring, so that, similar to biological evolution, only the fit individuals survive and proliferate. Note that the selection, crossover, and mutation probabilities define the trade-off between explorative and exploitative behavior. For instance, a strategy with higher mutation than crossover probability leads to an explorative behavior that prefers to generate new solutions instead of optimizing the current ones. Similarly, a selection operator that tends to always discard unfit chromosomes leads to an exploitative behavior that prefers inbreeding to outbreeding. There exists a number of free and commercial libraries, available in several programming languages, which implement GA: notable examples include OPEN

BEAGLE[14], the Genetic Algorithms Utility Library (GAUL)[15], the Java Genetic Algorithms Package (JGAP)[16], and the Genetic Algorithms Library (GALIB)[17].

GA have been used for many activities in SBST, including the generation of workloads that represent worst-case scenarios with respect to task deadlines [Briand et al., 2005]. Recall from Section 2.3.2 that generating stress test cases that push a system into violating performance requirements is challenging because of the large set of possible scenarios where task can interact, and the complex nature of RTES which renders such task interactions unpredictable. Therefore, it is a natural choice to cast this problem as a search problem, and solve it through the use of metaheuristics. The key idea that enables the use of GA is to model the arrival times of aperiodic system tasks as chromosomes, and to evaluate their fitness by computing the value of a function that properly rewards scenarios with deadline misses. This fitness function depends on the end times of tasks, which can be calculated starting from a fixed arrival pattern. Indeed, the fitness of each chromosome is calculated by simulating the schedule that the Real-Time Operating System produces in case of the arrival pattern specified by the chromosome. We present below a brief description of this GA-based approach for stress testing of task deadlines [Briand et al., 2006].

- **Population, Chromosomes, and Genes.** The initial population consists of 80 chromosomes, where each chromosome represents a set of arrival times for aperiodic tasks, i.e., an arrival pattern for the RTES. Each gene in the chromosome is encoded as the pair (j_k, t), where j_k is the k^{th} execution of task j, and t is the arrival time of j_k.
- **Crossover Operator.** The algorithm uses with 0.7 probability a n-point crossover operator, where n is the number of aperiodic tasks. Each crossover point is defined after the set of genes corresponding to an aperiodic task. In this way, chromosomes cross over exchanging genes associated to the same task. Each crossover produces two offspring, where the genes of the parents are inherited by the offspring with 0.5 probability, in a way that the children inherit each gene from a different parent. Note that, due to real-time constraints, two consecutive arrival times of each aperiodic task must be separated by its minimum and maximum interarrival times. During the search, it may happen that a crossover operation breaks this constraint on a certain chromosome. In such case, the algorithm invalidates the operation, and proceeds by applying it to a different chromosome.
- **Mutation Operator.** The genes in the chromosome are mutated by randomly replacing one arrival time. This replacement is done by generating a time value in the interval defined by the minimum and maximum interarrival times of the preceding task execution. The mutation operator is applied at each gene with a probability of $1.75 \cdot (\lambda\sqrt{l})^{-1}$, where λ is the population size, and l is the length of the chromosomes.

The population size, and the crossover and mutation rates, have been derived from the literature of GA and tuned for the specific domain of deadline miss analysis [Briand et al., 2005]. This GA-based approach uses the GALIB implementation, and has been successfully used to generate stress test cases in

[14] `http://code.google.com/p/beagle/`
[15] `http://gaul.sourceforge.net/`
[16] `http://jgap.sourceforge.net/`
[17] `http://ancet.mit.edu/ga/`

a case study from the avionics domain featuring the weapon control system of a military aircraft [Locke et al., 1990].

Chapter 3

Problem Description

Real-Time Embedded Systems (RTES) are becoming increasingly more complex and critical in many industry sectors. A main aspect of such complexity is their concurrent architecture that entails that several tasks are triggered and executed in parallel in ways which are difficult to establish *a priori* [Gomaa, 2006]. Moreover, RTES are often safety critical [Kopetz, 2011], and thus bound to meet strict performance requirements. In addition, their tasks must satisfy execution constraints in terms of dependency from shared computational resources, triggering of other tasks, maximum completion time, and execution priority. Such complexity gives rise to a multitude of possible task execution scenarios at runtime, for which any manual reasoning is very inefficient, if not infeasible. In the domain of safety-critical RTES one is especially interested in those particular scenarios that exercise a system in a way that tasks are pushed as close as possible to violate their performance requirements. Identifying such scenarios is the basis for stress testing, a high-priority activity in the validation of RTES [Beizer, 2002]. In the rest of this chapter, we will first introduce the principles behind stress testing through an abstract example (Section 3.1), and then we will discuss the problem concretely in an industrial case study from the maritime and energy domain (Section 3.2).

3.1 Finding Worst-case Scenarios in Real-Time Embedded Systems

Most of the approaches for analyzing time-related properties in RTES are based on a combination of real-time scheduling theory (Section 2.1.1) and static Worst-case Execution Time (WCET) analysis (Section 2.1.2). These methods estimate the schedulability of a tasks set under a given scheduling policy [Tindell and Clark, 1994], assuming worst case situations with respect to tasks arrival times, and using estimates for task execution times [Baker, 2006]. For instance, the Completion Time Theorem (CTT) provides a sufficient condition for deadlines to be met in case of a task set of independent tasks scheduled with the Rate Monotonic algorithm [Lehoczky et al., 1989]. The CTT specifies that, if each task meets its deadline when all tasks start executing at the same time, then the tasks will meet their deadlines for any combination of start times. The CTT assumes that task do not depend on each other, which is hardly the case in large and complex RTES. For this reason, the CTT has been extended into the Generalized Completion Time Theorem (GCTT) by considering interdependent tasks that share resources with exclusive access [Gomaa, 2006]. Note that both the CTT and the GCTT only consider periodic tasks. For scheduling analysis, the GCTT has been extended to also consider aperiodic tasks [Sha and Goodenough, 1989]. In this extension, aperiodic tasks are considered as periodic tasks with period equal to their maximum interarrival time [Sprunt et al., 1989]. The CTT and the GCTT both consider that the worst-case scenario with respect to task deadlines is the case where all tasks are simultaneously ready to execute when the system starts. However, this does not hold when both interdependent and aperiodic tasks are present. Consider for instance a *fixed-priority preemptive scheduler* that schedules the task set $J = \{j_1, j_2, j_3\}$ described in Table 3.1. The first row reports the observation interval T of the task set, and the number c of cores of the target platform, i.e., the maximum number of tasks that can run in parallel. The first columns of the table report the tasks priority, duration, period, minimum and maximum interarrival times, and deadline. The last two columns report triggered tasks, and tasks that share computational resources with exclusive access. A centered dot ($\cdot$) indicates that the property does not hold for a task. For example, j_0 is periodic, and therefore does not have minimum and maximum interarrival times. Similarly, j_0 triggers j_1 upon finishing execution, and does not share computational resources with other tasks. Note that, as it often happens in RTES analysis, time is discretized into *time quanta*. This means that time-related properties of tasks are expressed as multiples of a time quantum. In the example, T is an integer interval of 9 time quanta.

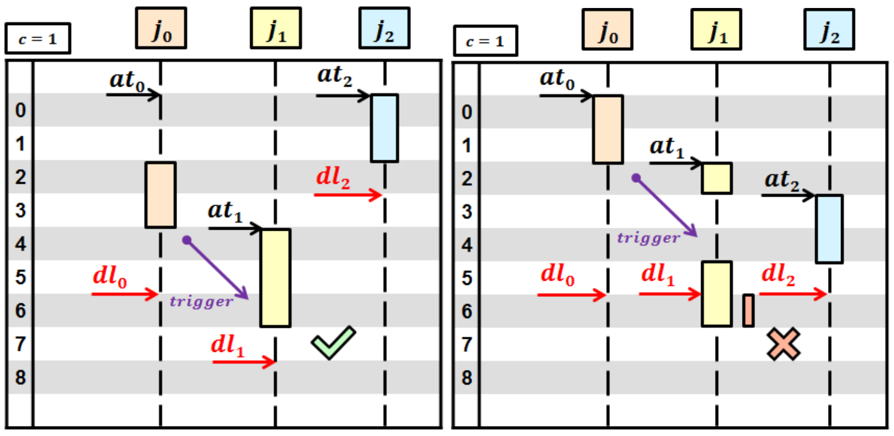
		$T = [0, 8]$				$c = 1$		
Task	priority	duration	period	min_ia	max_ia	deadline	triggers	depends
j_0	0	2	9	$\cdot$	$\cdot$	6	j_1	$\cdot$
j_1	1	3	$\cdot$	$\cdot$	$\cdot$	4	$\cdot$	$\cdot$
j_2	2	2	$\cdot$	9	9	3	$\cdot$	$\cdot$

Table 3.1. Example system with three tasks, one of which is triggered

In this task set, j_0 is a periodic task that triggers j_1, and j_2 is a higher priority aperiodic task. The GCTT assumes that the worst-case scenario happens when j_0 and j_2 arrive simultaneously at the beginning of the observation interval. Note that this scenario does not lead to any deadline miss, as showed in Figure 3.1.1. However, there exists a scenario where j_1 misses its deadline: this happens if j_2 arrives after j_0 has finished, as depicted in Figure 3.1.2. Note that similar examples can also be made for response time and CPU usage.

This example shows two important concerns when analyzing time-related properties of RTES. First, it shows how the GCTT result, i.e., that the worst-case scenarios happen when each task arrives simultaneously at the beginning of the observation interval, is not valid when tasks have complex dependencies. Second, the example shows how the task arrival times have a great impact on hard real-time properties, and specifically, on deadline constraints. Note that arrival times of aperiodic tasks depend on the environment, and can never be predicted prior to the execution of the system. Indeed, the arrival times also vary across different system executions due to the unpredictability of the environment.

For the reasons above, in order to evaluate deadline miss constraints, we need a strategy to search for



(3.1.1) j_0 and j_2 arrive simultaneously, but no task misses its deadline (3.1.2) j_2 arrives when j_1 is executing, and makes it miss its deadline

Figure 3.1. Impact of changes in the arrival times of tasks with respect to deadline miss properties

all the possible task arrival times. The search has to be performed in an effective way with the objective of finding scenarios that violate performance requirements or are close to violating them. In software formal verification, time-related properties expressed in a RTES models have been successfully verify with Model Checking (MC) approaches [Alur et al., 1990]. Such properties typically represent conditions, e.g., deadline misses, that should never hold in the system at any given time. Usually, MC approaches cast the search of these properties as a reachability query over a Finite State Machine representing the system behavior. However, MC is mostly used for *verification*, i.e., to check if a given set of real-time tasks satisfy some property of interest. In general, one wants to complement formal design verification by testing the system implementation, which is the focus of this thesis. Specifically, we focus on the problem of identifying scenarios that exercise a system in a way that tasks are pushed as close as possible to violate their performance requirements on deadlines, response time, and CPU usage. Consistent with the widely accepted definition [Beizer, 2002], we refer to this activity as *stress testing* (Section 2.3.2). Specifically, given a performance requirement, we define a *stress test case* as a sequence of arrival times for aperiodic tasks that the search identifies as likely to violate that performance requirement.

The ultimate goal of this thesis is to define an efficient and effective strategy for the generation of stress test cases. To do so, we have devised an approach based on UML/MARTE modeling (Chapter 5), where the search for arrival times of aperiodic tasks is carried out by a strategy where Constraint Programming (CP) (Chapter 6) is combined with Genetic Algorithms (GA) (Chapter 7).

3.2 Motivating Case Study

The main motivation behind the work described in this thesis comes from the case study in the maritime and energy domain concerning a Fire and gas Monitoring System (FMS). The FMS is developed by Kongsberg Maritime (KM)[1], a leading company in the production of systems for positioning, survey-

[1]www.km.kongsberg.com

ing, navigation, and automation to merchant vessels and offshore installations. The goal of the system is to monitor potential gas leaks in oversea oil extraction platforms, and trigger an alarm in case a fire is detected. The system monitors and displays to human operators data coming from smoke detectors, heat detectors, and gas flow sensors. When the system receives some critical data from the hardware sensors, it automatically triggers actuators, such as fire sprinklers and audio/visual alarms. Technicians constantly monitor the system, and can also directly interact with it, for instance to manually tune operational parameters or control events raised by specific data. The FMS software architecture is shown in Figure 3.2.

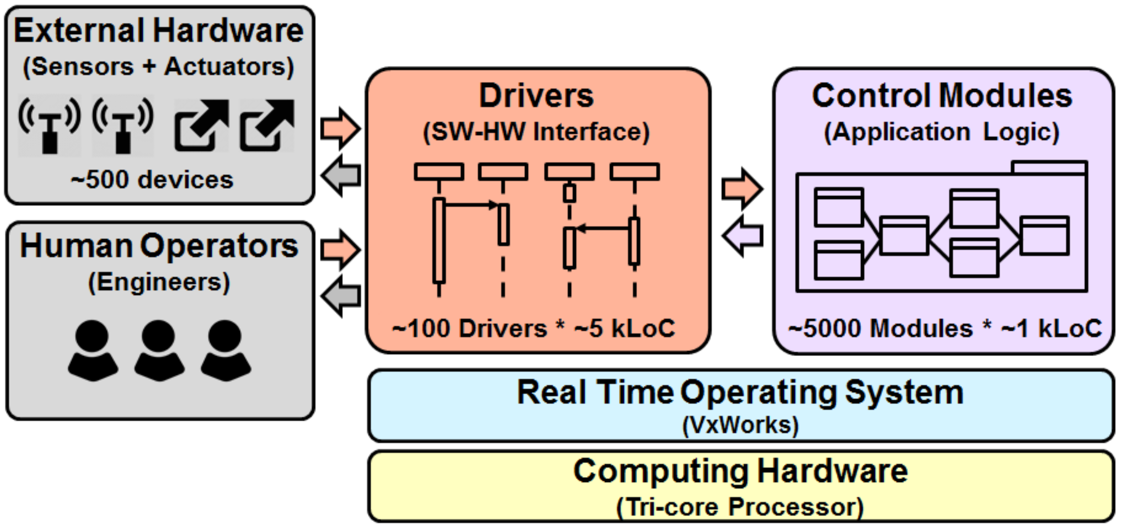


Figure 3.2. The architecture of the Fire and Gas Monitoring System (FMS)

The software part of the system consists of a set of drivers, and a set of control modules. Drivers implement I/O communication between the system and the external environment, such as hardware sensors, actuators, and human operators. Control Modules implement the application logic of the FMS, i.e., they process data coming from the environment and accordingly decide the operations to perform. Drivers and Control Modules are the main software components of the FMS, and run on a Real-Time Operating System that is executed over a multicore computing platform. The whole FMS is composed by approximately 5000 control modules and 500 sensors and actuators that communicate with the system through ca. 100 different drivers. Drivers and control Modules have an approximate size of 5 and 1 thousands lines of source code (kLoC) each. The system runs on a Real-Time Operating System (RTOS), namely VxWorks[2], that is configured with a fixed-priority preemptive scheduling policy. VxWorks is installed on a platform featuring a tri-core processor. This architectural design is common in many industry sectors relying on embedded systems [Buttazzo, 2011].

Figure 3.3 shows the key entities of the FMS which are relevant to our study. A communication scenario consists in a driver communicating externally with some sensors and/or actuators, and communicating internally with control modules. To cope with the large number of external hardware devices,

[2] `http://www.windriver.com/products/vxworks`

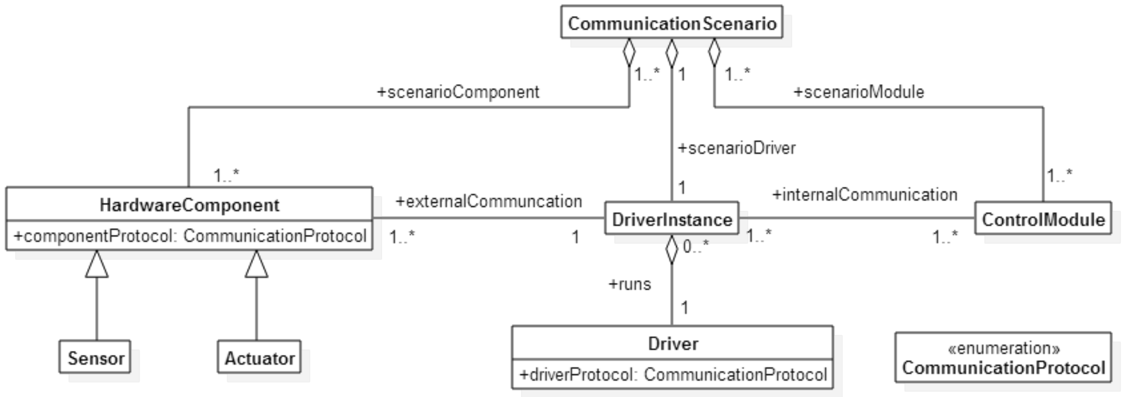


Figure 3.3. A class diagram representing the key entities in the Fire and Gas Monitoring System (FMS)

the system runs in parallel several instances of each driver. In the FMS, each driver implements a specific communication protocol, and it is meant to communicate only with sensors and actuators that implement the same protocol. The reason for having different types of drivers relies in the variety of sensors and actuators built by different vendors. Indeed, devices work under specific communication protocols that have to be implemented by the drivers in order to successfully connect the devices to the system.

Drivers constitute the most critical part of the FMS. Indeed, one of the main complexity factors in drivers is that they are meant to bridge the timing discrepancies between hardware devices and software controller modules. Hence, their design typically consists of parallel tasks that communicate asynchronously to smooth the data transfer between hardware and software. Therefore, drivers are subject to strict requirements to ensure that their flexibility does not come at the cost of performance. Specifically, in each FMS driver (1) no task should miss its deadline, (2) the response time should be less than 1 second, and (3) the CPU usage should be below 20%.

Three important context factors in the FMS case study influenced the definition of our approach to generate stress test cases. (1) Different instances of a given driver are independent, in the sense that they do not communicate with one another and do not share memory. (2) The purpose of the constraint on CPU usage is to enable engineers to estimate the number of driver instances of a given monitoring application that can be deployed on a CPU. These constraints express bounds on the amount of CPU time required by one driver instance. Therefore, in this thesis we focus on individual driver instances. The independence of the drivers (first factor above) is the key to being able to localize CPU usage analysis to individual instances in a sound manner. (3) The drivers are not *memory-bound*, i.e., task deadlines, response time, and CPU usage, are not significantly affected by activities such as disk I/O and garbage collection. To ensure this, KM over-approximates the maximum memory required for each driver instance by multiplying the number of hardware devices connected to the driver instance and the maximum size of data sent by each device. Execution profiles at the partner company indicate that the drivers are extremely unlikely to exceed this limit during their lifetime.

Figure 3.4 shows the an a example of three communication scenarios in the FMS, represented by a dashed rectangle. In the scenario at the top, the instance i_1 of driver d_1, which implements the protocol

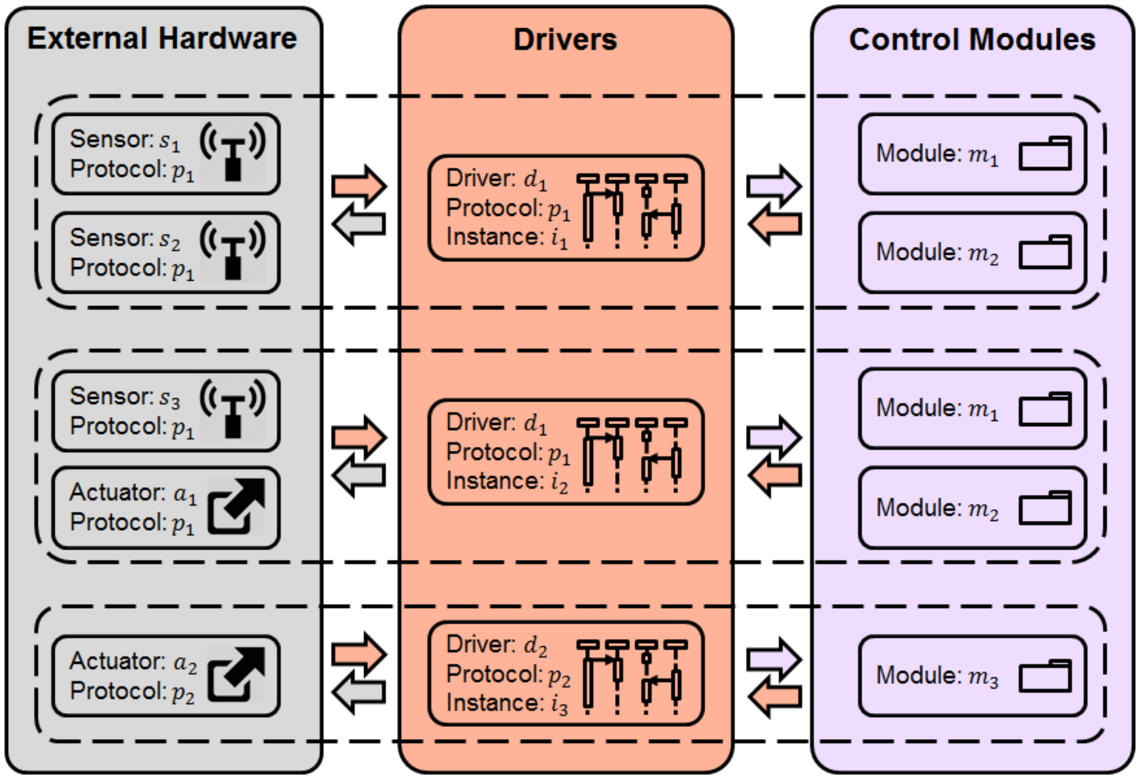

External Hardware
Drivers
Control Modules
Sensor: s_1 Protocol: p_1
Sensor: s_2 Protocol: p_1
Driver: d_1 Protocol: p_1 Instance: i_1
Module: m_1
Module: m_2
Sensor: s_3 Protocol: p_1
Actuator: a_1 Protocol: p_1
Driver: d_1 Protocol: p_1 Instance: i_2
Module: m_1
Module: m_2
Actuator: a_2 Protocol: p_2
Driver: d_2 Protocol: p_2 Instance: i_3
Module: m_3

Figure 3.4. An example showing three communication scenarios in the Fire and Gas Monitoring System (FMS)

p_1, communicates with the sensors s_1 and s_2 and the control modules m_1 and m_2. In the scenario at the center, the instance i_2 of d_1 communicates with the sensor s_3, the actuator a_1, and the modules m_1 and m_2. In the scenario at the bottom, the instance i_3 that runs the driver d_2 communicates with the actuator a_2 and the module m_3. Note that, in each scenario, the driver implements the same communication protocol of the sensors and actuators involved.

Drivers in the FMS share the same design pattern, where periodic and aperiodic tasks communicate asynchronously through buffers. There exist two major types of driver implementations, one with four aperiodic tasks (Section 3.2.1), and another with a singular task consisting of four activities in an infinite loop (Section 3.2.2)[3]. However, regardless of the implementation, all the drivers have to satisfy the same performance requirements. Nonetheless, the specific factors determining whether or not the performance requirements will be satisfied at runtime closely depend on the specific implementation used.

3.2.1 Implementation 1: Data Transfer with Four Aperiodic Tasks

The first implementation of the FMS drivers consists of six tasks communicating through three buffers. More precisely, in this implementation a generic driver consists of:

[3] Recall from Section 2.1.1 that a singular task is executed only once during the system execution, and that an activity represents a sequence of operations that a task executes.

- Three communication buffers, namely *BoxIn*, *Queue*, and *BoxOut*. These buffers serve as temporary storage locations for the data transiting from the hardware devices to the control modules. Moreover, the buffers have a fixed capacity, and exclusive access by software tasks, i.e., no two task can simultaneously access a buffer. *BoxIn* and *BoxOut* contain formatted data that is coming from the external hardware, and going towards the control modules respectively. *Queue* contains a priority-ordered list of commands extracted from the data that have to be processed by the control modules.
- Two periodic tasks, namely *PullData* and *PushData*. These tasks are periodically activated by a *scan* signal, and transfer data from the hardware sensors, and to the control modules respectively.
- Two aperiodic tasks, namely *IOBoxRead* (*IOBR*) and *IOQueueRead* (*IOQR*). These tasks are activated at irregular interval of times by a *check* signal that is fired by the RTOS to notify that *BoxIn* and *Queue* are almost full and need to be emptied.
- Two tasks triggered by aperiodic tasks, namely *IOQueueWrite* (*IOQW*), and *IOBoxWrite* (*IOBW*). These tasks are activated by a *trigger* signal from *IOBoxRead* and *IOQueueRead* respectively, when they finish reading from the *BoxIn* and *Queue* buffers.

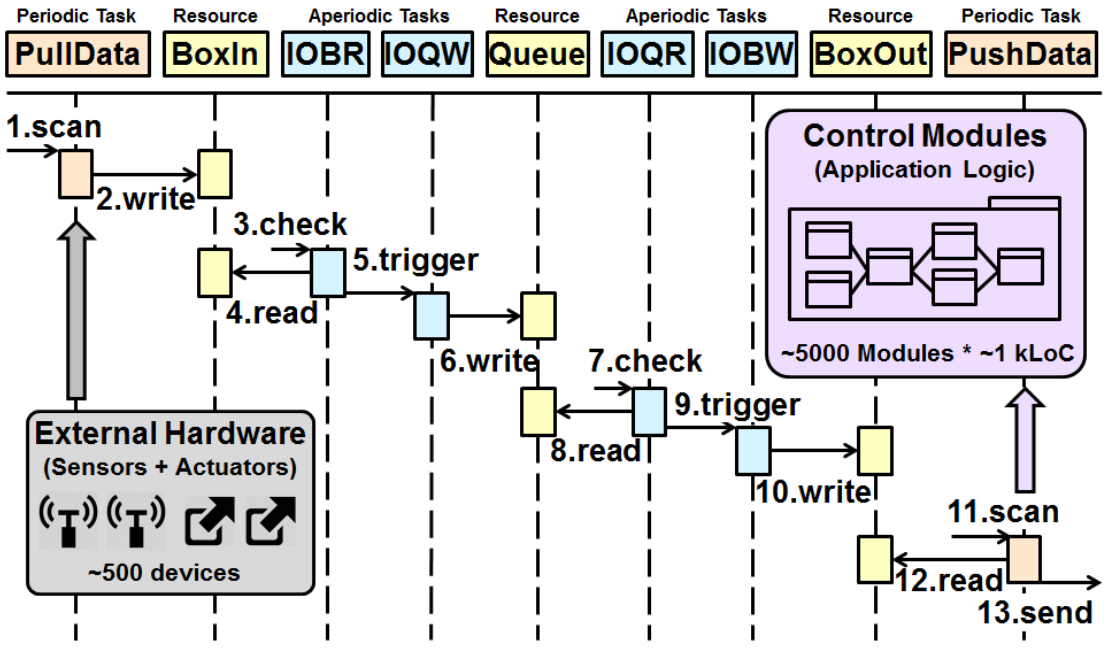


Figure 3.5. A typical operating scenario of drivers in the FMS consisting of a unidirectional data transfer between external hardware sensors and control modules. The scenario is implemented by two periodic tasks, four aperiodic tasks, and three buffers.

Figure 3.5 shows how tasks in the first driver implementation collaborate in the typical scenario, that is a unidirectional data transfer between hardware sensors and control modules. (1) *PullData* periodically receives data from sensors or human operators, formats the data in an appropriate command form, and (2) writes it in the buffer *BoxIn*. (3) When *BoxIn* is almost full, the *check* signal activates *IOBoxRead* that (4) reads the data from the buffer and (5) triggers *IOQueueWrite*. *IOQueueWrite* extracts the commands from the data, and (6) stores them in the priority *Queue*. When *Queue* is reaches a critical capacity,

(7) the *check* signal activates *IOQueueRead* that (8) reads the highest priority command and (9) triggers *IOBoxWrite* which in turn (10) writes the command to *BoxOut*. When the periodic *scan* signal (11) activates *PushData*, the task (12) reads the commands from *BoxOut* and finally (13) sends them to the control modules for processing.

As mentioned before, this asynchronous design is necessary for the drivers to smooth the data transfer between external devices and control devices. However, the data transfer functionality is subject to strict performance requirements in terms of task deadlines, response time, and CPU Usage. Specifically, (1) each of the six tasks that implement a driver has to finish before its deadline, typically in the range of milliseconds. Consider for instance a scenario where *PushData* is blocked on the *BoxOut* driver by *IoBoxWrite*, and thus is late in alerting the control modules that a fire has been detected. In this case, the system will fail to timely activate the alarm and the sprinklers, with potential severe consequences. Task deadlines are hard real-time constraints that have to be met to ensure that the system safely reacts in case of fire. However, the FMS is also subject to soft-real time constraints such as (2) response times. Indeed, the interval of time between an execution of *PullData* and the execution of *PushData* that sends the commands to the control modules has to be bounded. Consider for instance a scenario in which some data in *BoxIn* is not promptly emptied. If too much time passes after that data is collected by the external hardware, the new data arriving from the same sensor will arrive when the old data has still not been processed. Therefore, the FMS will perform the commands corresponding to the first chunk of data when the environment state has already changed. This behavior degrades the QoS, as the system will not react promptly to external changes. Finally, driver instances are independent from each other, and thus concurrently executed in the same hardware platform. For this reason, (3) each driver instance must not exceed a given threshold of CPU usage. Indeed, if a driver has a significant impact on the CPU time, other driver instances may have to wait too long for the operative system to grant them computational resources and potentially fail to timely process critical data.

The main variables determining whether or not these requirements is satisfied at runtime are the arrival times of the *check* signal. These arrival times depend on the environment, in the sense that they depend on the data sent by the hardware sensors via *PullData*. The arrival times also vary across different system executions, as a consequence of the impossibility to predict the data coming from the sensors. Therefore, in order to evaluate task deadlines, response time, and CPU usage, we need a strategy to search for all the possible task arrival times. The search has to be performed in an effective way with the objective of finding scenarios that are predicted to violate the requirements, or be close to violating them. Indeed, the more likely is a scenario predicted to violate a performance requirement, the higher the chances that the test case characterized by such scenario stresses the system.

3.2.2 Implementation 2: Data Transfer with One Singular Task and Four Activities

There also exists a second implementation of the FMS drivers, where the functionalities of *IoBoxRead*, *IoBoxWrite*, *IoQueueRead*, and *IoQueueWrite* are implemented in four *activities* of a singular task, namely *IoDispatch*. *IoDispatch* encloses the four activities in an infinite loop, and sequentially executes them. The activities that read *BoxIn* and write *Queue* are separated by the activities that read *Queue* and write *BoxOut* by a *delay* time. The delay ensures that the control modules receive data from the sensors at a slow enough rate so that the FMS can process it. Note that the delay time typically corresponds to a *sleep* call in the drivers source code. Also note that *IoDispatch* is executed only once, in particular when the system starts. Even though *IODispatch* is formally a periodic task, its behavior is determined by the delay time between activities at each loop iteration.

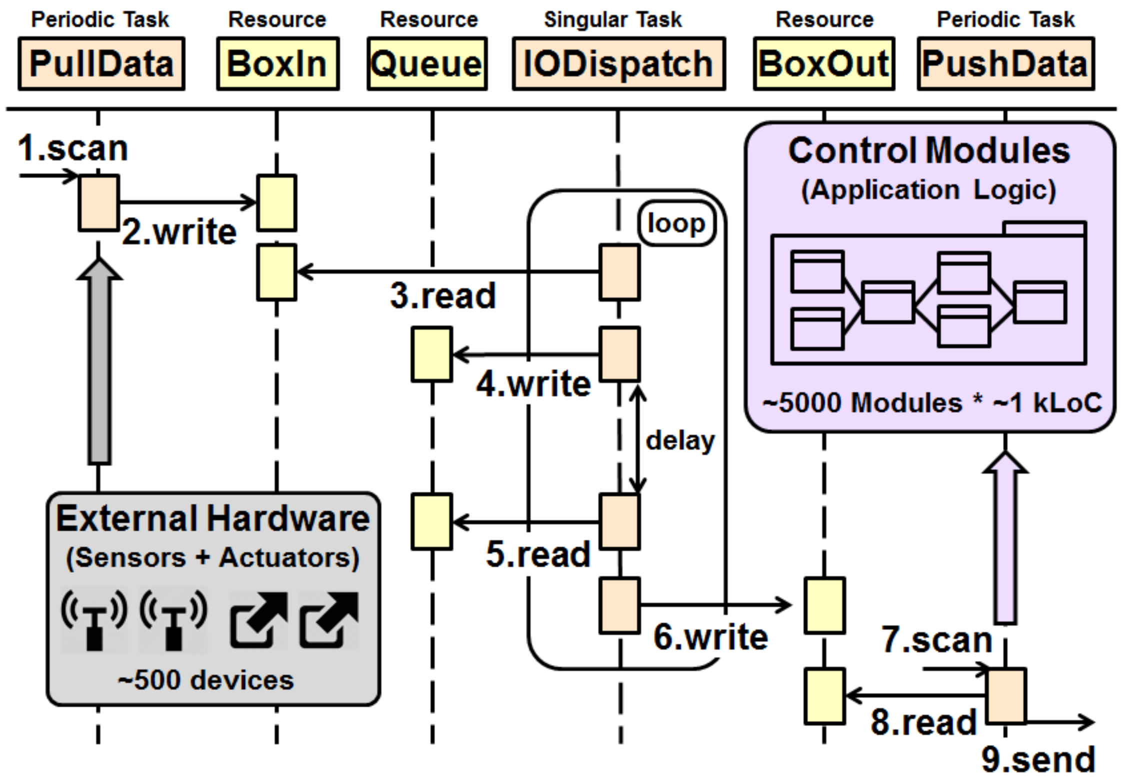


Figure 3.6. The unidirectional data transfer scenario between external hardware sensors and control modules implemented by two periodic tasks, an aperiodic task enclosed in an infinite loop, and three buffers.

Figure Figure 3.6 shows how tasks in the second driver implementation collaborate in the scenario of a unidirectional data transfer between hardware sensors and control modules. (1) *PullData* periodically receives data from sensors or human operators, formats the data in an appropriate command form, and (2) writes it in the buffer *BoxIn*. (3) *IoDispatch* reads the data from the buffer, extracts the commands from the data, and (4) stores them in the priority *Queue*. After a given delay time, (5) *IoDispatch* reads the highest priority command and (6) writes it to *BoxOut*. When the periodic *scan* signal (7) activates *PushData*, the task (8) reads the commands from *BoxOut* and finally (9) sends them to the control modules for processing.

There exists a fundamental difference between the first drivers implementation described in Section 3.2.1, and this second one. In the former, as explained before, the main variables determining whether or not the driver performance requirements are satisfied at runtime are the arrival times of the *check* signal. However, in the second implementation the arrival times of *IoDispatch* do not have significant impact on the performance requirements. This is because the task arrives only once, and when the system is started. In this case, the delay times between the first and the last two activities of *IoDispatch* determine whether or not the driver satisfies its performance requirements at runtime. Indeed, if the delay times are too short, *IoDispatch* is continuously running and keeps the CPU busy, eventually exceeds the given threshold on CPU usage. On the other hand, if the delay times are too large, *pullData* may fill up *BoxIn*, and be blocked waiting for *IODispatch* to empty the buffer. As a result, *pullData* is not able to terminate before its next *scan* signal arrives, missing its deadline.

Opposite to the arrival times in the first implementation, the delay times do not depend on the environment, but rather are tunable parameters that engineers can choose when configuring the system. Therefore, in order to evaluate task deadlines, response time, and CPU usage in this second implementation, we need a strategy to search for all the possible task delay times. Note that the objective of the search remains finding scenarios that are predicted to violate the requirements, or be close to violating them. The difference with the search in the case of the first implementation lies within the choice of the variables to search for.

The problem of ensuring that performance requirements are satisfied in the second drivers implementation leads to a definition of stress test cases which is different from the one given at the end of Section 3.1. Indeed, in this second drivers implementation, a stress test case with respect to a performance requirement is a sequence of delay times (rather than arrival times) likely to violate that performance requirement. These stress test cases retain the traditional goal of stress testing, i.e., ensuring that the system satisfies the performance requirements even under the worst operating conditions. However, these test cases identify values for tunable parameters (rather than replicable environmental conditions) that violate the requirements. Therefore, the execution traces of these stress test cases can be used to ensure that upon configuration the parameter values remain within safe margins. Note that, on the other hand, execution traces of stress test cases characterized by arrival times have to be carefully analyzed together with the system architecture, in order to find possible bottlenecks hindering the system performance. We finally point out that, for the rest of this thesis, we are consistent with the traditional meaning of stress testing in RTES with respect to environmental conditions, and hence with the definition of stress test cases given at the end of Section 3.1. Recall from Section 2.1.1 that indeed, for scheduling analysis, each activity can be considered as a task, provided that the RTOS overhead for managing tasks in negligible with respect to their execution and interarrival times. For this reason, when not specified otherwise, stress test cases are characterized by sequences of arrival times for aperiodic tasks.

Part II

Approach and Discussion

Chapter 4

Automating the Generation of Stress Test Cases in Real-Time Embedded Systems: an Overview

In this thesis, we present an approach for generating stress test cases exercising performance requirements of RTES. The framework blends UML/MARTE modeling to capture the timing and concurrency aspects of the system design and platform, and automated search based on Genetic Algorithms (GA) (Section 2.4.2.2) and Constraint Programming (CP) (Section 2.4.1) to generate the stress test cases. An overview of the approach is shown in Figure 4.1.

The approach builds upon a conceptual model that captures details about the timing and concurrency aspects in the software components and computing platform of the RTES. Specifically, the conceptual model captures abstractions in the software application, e.g., tasks with their priorities, periods, dependencies, and in the computing platform, e.g., processing cores and scheduling policies. Entities in this conceptual model are mapped to MARTE stereotypes, thus defining a subset of the profile which is relevant for supporting the generation of stress test cases. In particular, the abstractions related to the software application are mapped to stereotypes that extend UML metaclasses represented in sequence diagrams. Note that sequence diagrams are popular for visualizing concurrent multi-threaded interactions, and are intuitive to most developers [Harel and Marelly, 2003]. On the other hand, abstractions in the conceptual model related to the computing platform are mapped to stereotypes that extend generic UML metaclasses, which can be represented in class or deployment diagrams. We validate the conceptual model in the Fire and Gas Monitoring System (FMS) introduced in Section 3.2, showing that it can be applied in an industrial setting with a practically reasonable overhead. The conceptual model and its mapping to MARTE have been first introduced in a conference paper [Nejati et al., 2012], and is discussed in Chapter 5.

Design and platform models stereotyped with MARTE organize the input data for our approach, which generates stress test cases using automated search. Specifically, we cast the generation of stress test cases as an optimization problem over the abstractions represented in design and platform models. The goal of the optimization problem is finding arrival times for aperiodic tasks that maximize the likelihood

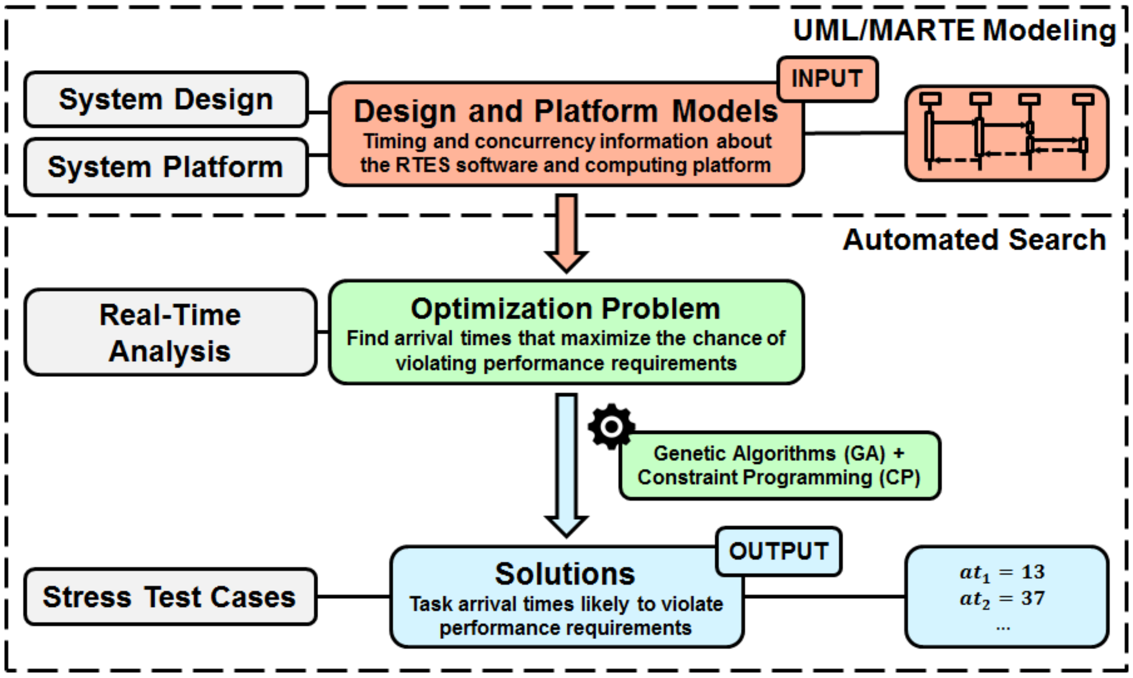

UML/MARTE Modeling
System Design
System Platform
INPUT
Design and Platform Models
Timing and concurrency information about the RTES software and computing platform
Automated Search
Real-Time Analysis
Optimization Problem
Find arrival times that maximize the chance of violating performance requirements
Genetic Algorithms (GA) + Constraint Programming (CP)
OUTPUT
Stress Test Cases
Solutions
Task arrival times likely to violate performance requirements
$at_1 = 13$
$at_2 = 37$
...

Figure 4.1. An overview of our approach for generating stress test cases in Real-Time Embedded Systems.

of the RTES violating its performance requirements on task deadlines, response time and CPU usage. To solve this optimization problem, we discuss a search strategy based on CP. Specifically, we present a Constraint Optimization Model (COP) that models the system design, real-time properties, executing platform, and performance requirements. The COP is implemented as an Optimization Programming Language (OPL) model, which is solved with IMB ILOG CPLEX CP OPTIMIZER. We validate our CP-based search strategy in the FMS, showing that CP is able to effectively identify arrival times for aperiodic tasks that are predicted to maximize deadline misses, response time and CPU usage. We also compared CP with GA in five systems from safety-critical domains, analyzing both strategies in terms of the trade-off between the time needed to generate stress test cases, and their power for revealing worst-case scenarios with respect to task deadlines. The CP-based strategy has been first introduced in a workshop paper [Di Alesio et al., 2012], and in three conference papers [Nejati et al., 2012, Di Alesio et al., 2013, Di Alesio et al., 2014], and is discussed in Chapter 6.

The series of experiments to evaluate the performance of CP and GA shows an opposing trend. Specifically, GA is more *efficient*, i.e., faster in generating test cases, while CP is more *effective*, i.e., it generates test cases that are more likely to reveal deadline misses. In practice, it is also important to evaluate to what extent the test cases generated by an approach exercises different aspects of the system under test. This concept is commonly known as *test coverage*, and is an important metric to assess the quality of a test suite (Section 2.3). In these experiments GA generated a large number of test cases that were also highly *diverse*, i.e., they had a higher variety in terms of (1) time span, (2) preemptions between task executions, and (3) number of aperiodic task executions. On the other hand, CP generated fewer solutions which were mostly redundant. At a high level of abstraction, the experiments show that GA provides more coverage than CP due to the higher diversity in the test cases generated. For this reason, in this thesis we propose a strategy (GA+CP), based on the combined use of GA and CP, aimed at holding both the efficiency and solutions diversity of GA and the effectiveness of CP. The choice of combining the two search strategies has been motivated by the analysis of the results of our previous experiments. Specifically, we looked into the possibility of further improving the solutions computed by GA by performing a complete search with CP in their neighborhood. In this way, GA+CP takes advantage of the efficiency of GA, because solutions are initially computed with GA, and the subsequent CP search is likely to terminate in a short time since it focuses on the neighborhood of a solution, rather than on the entire search space. GA+CP also takes advantage of the diversity of the solutions found by GA, because CP performs a local search in subspaces defined by GA solutions. Similarly, GA+CP takes advantage of the effectiveness of CP since, once GA has found a solution, CP further improves it by either finding the best solution within the neighborhood, or proving upon termination that no better solution exists. GA+CP has first been introduced in a journal paper [Di Alesio et al., 2015], and is discussed in Chapter 7.

Chapter 5

Modeling Real-Time Embedded Systems with UML/MARTE to Support Stress Testing

Recall from Section 2.2.2.3 that UML/MARTE defines a large number of abstractions related to RTES performance. Even though these abstractions support the definition of methodologies for performance analysis and verification, MARTE does not include guidelines on how to identify the relevant stereotypes and tagged values for a particular kind of analysis. In this section, we propose a conceptual model that captures, independently from any modeling language, the abstractions required to support stress testing in RTES (Section 5.1). To simplify the application of our conceptual model in Model-Driven Engineering (MDE) approaches, we propose a mapping of our conceptual model to UML/MARTE (Section 5.2). Note that we define the abstractions needed to support stress test cases in two steps, i.e., first defining a conceptual model, and then its mapping to MARTE. This formalization approach is similar to the one in MARTE, where concepts related to RTES are first defined a domain model, and then formalized as stereotypes and tagged values in a UML representation (Section 2.2.2.3). Finally, we validate the conceptual model in the Fire and Gas Monitoring System (FMS) described in Section 3.2. The validation shows that the conceptual model and its mapping to UML/MARTE can be applied with a practically reasonable overhead in an industrial context (Section 5.3).

5.1 A Conceptual Model to Support Stress Testing in Real-Time Embedded Systems

To enable a sound definition of our approach, we first define a conceptual model that identifies the key abstractions of RTES that are relevant for stress testing. Note that, even though RTES share some commonalities, they all require domain-specific configurations. This means that, we need to define a conceptual model that captures the abstractions required for stress testing independently from specific contexts. Recall from Section 3.1 that the goal of our approach is finding worst-case scenarios for RTES tasks that are likely to violate task deadlines, response time, and CPU usage constraints. Therefore, our conceptual model is based upon abstractions defined in the real-time scheduling theory (Section 2.1.1), such as tasks, activities, and scheduling policies. Figure 5.1 shows an overview of the conceptual model we propose, whose entities are explained below. Classes in the conceptual model are partitioned into the *Application* and *Platform* packages, which respectively correspond to the system design and platform of Figure 4.1.

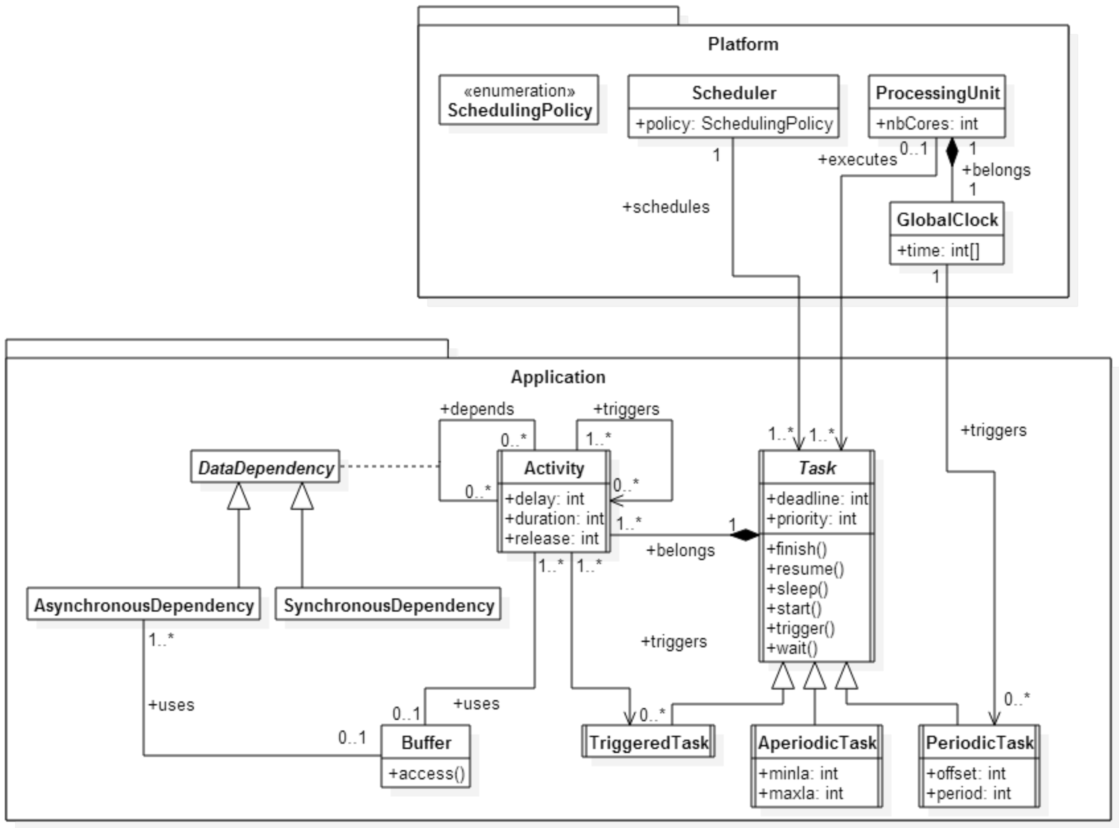


Figure 5.1. Our conceptual model representing the key abstractions to support stress testing in Real-Time Embedded systems.

- **Application.** The software part of a RTES is an embedded application, which consists of several parallel software *tasks*, and is allocated in a *computing platform.*
  - **Activity.** Recall from Section 2.1.1 that an activity is a sequence of operations in a task, and that task activities within a task are sequentially executed. Each activity a has an estimated *duration* or Worst-Case Execution Time (WCET). Consecutive activities within a task are separated by a *delay* time, and each activity starts executing after a given *release*. Activities can *trigger* other activities: for example, each activity in a task triggers the following one, thus defining a temporal ordering. This is because after the last statement in an activity is executed, the program control flow executes the first statement in the following activity. Activities can also trigger other tasks: for example, upon meeting certain conditions, an activity can spawn a new task to perform additional operations. Moreover, activities in a task can also *depend* on each other by sharing computational resources which are generally used for communication.
  - **DataDependency.** Activities can depend on each other because they communicate in a *synchronous* or *asynchronous* way.

- **Buffer.** Asynchronous communication between two activities can use a buffer, whose *access* is protected by semaphores, and hence is blocking. This means that at most one activity can access a buffer at any time. Note that, in this thesis, we only consider the case where tasks are communicating asynchronously through buffers.
- **Task.** The software part of a RTES consists of a set of parallel tasks that have to complete before a given *deadline*. Each task also has a *priority* that determines the relative importance of a task with respect to other tasks, so that the scheduler executes higher priority tasks before lower priority tasks. *Periodic* tasks are triggered by timed events handled by the global clock, and are invoked at regular intervals. Therefore, their arrival times are fixed, and equal to multiples of one interval, called *period*, which is counted starting from an *offset*. Periodic tasks are commonly used to send and receive data at regular interval of times, e.g., *PushData* and *PullData* in Figure 3.5. On the other hand, the arrival times for *aperiodic* tasks are bound by *minimum* and *maximum* inter-arrival times, which indicate the minimum and maximum time intervals between two consecutive arrivals of the event triggering the task. Aperiodic tasks are instead used to process asynchronous events/communications, e.g., *IODispatch* in Figure 3.5. Finally, the arrival time of *triggered* tasks is determined by particular activities, which spawn the task upon finishing their execution. During its lifetime, a task can perform the following operations.
  - *Trigger.* Communicates to the scheduler that the task is ready to start a new execution in response to a triggering event. The origin of the event depends on the type of the task. For periodic tasks, the event comes from an internal clock, for aperiodic tasks the event comes from the environment, and for triggered tasks the event comes from another task.
  - *Start.* Begins execution after having been assigned to a CPU core by the scheduler. This operation precedes the execution of the first activity of each task.
  - *Finish.* Completes execution. This operation is performed after the last activity in a task has completed.
  - *Wait.* Temporarily stops execution in order to synchronize with another task, or to acquire a resource. Note that each buffer access within an activity implies an implicit *wait* by its task.
  - *Sleep.* Temporarily stops execution for a given amount of time. Note that a *sleep* call for a given time t at the beginning (end) of an activity corresponds to a release (delay) for that activity equal to t.
  - *Resume.* Communicates to the scheduler that the task is ready to resume execution after a previous *wait* or *sleep* operation.

  The state machine in Figure 5.2 shows the lifecycle of a task, where the operations determine transitions between states. Tasks start in the *idle* state, and only consume CPU time in the *running* state. Note that there is no final state. This is common in embedded systems, which are intended to run continuously. Also note that, in our model, activities within tasks only release the CPU when preempted by the scheduler, so that the CPU can be used by another activity belonging to a higher priority task. This means that tasks perform the operations only between two consecutive activities.

- **Platform.** A computing platform is the hardware part of a RTES that executes embedded applications. A computing platform consists of a *processing unit*, and a real-time *scheduler*.

- **ProcessingUnit.** A processing unit represents the CPU of the computing platform. Each CPU has a *number of processor cores*, representing the maximum number of tasks that can be executed in parallel. Note that, as explained in Section 3.2, we do not consider memory such as RAM, disk memory, or cache in our conceptual model. This is because, given the context factors of this thesis, the impact memory has over task deadlines, response time, and CPU usage is negligible.
- **Global Clock.** The processing unit has a global clock, which determines when time-based events and triggers are fired. The global clock has a *time* attribute, representing a list of time instants where the system is running.
- **Scheduler.** The scheduler implements a given *scheduling policy*, which defines the rules to handle concurrency and execution order among tasks. Even though several policies are commonly used in RTES, in this thesis we only consider fixed-priority preemptive scheduling.

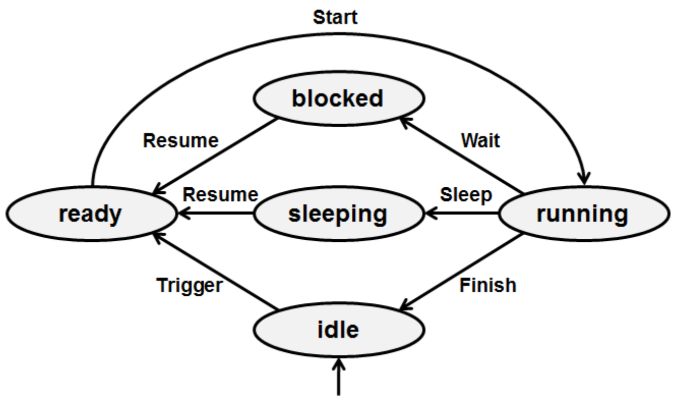


Figure 5.2. The state machine representing a task lifecycle. Events triggering a task determine a transition from the *idle* state to the *ready* state.

Note that, in our conceptual model, both tasks and activities are active objects, and hence are represented with double bars on the sides. Recall from Section 2.2.2.2 that active objects in UML model entities owning a process or thread, and that can initiate flow control activity.

5.2 Mapping of the Conceptual Model to UML/MARTE

To enable effective industrial use, every approach in software engineering has to be capable of seamless integration in the companies development cycle. Recall from Section 2.2 that, in the last years, Model Driven Engineering (MDE) has risen as a way to handle software complexity through the systematic use of models during development. In the context of RTES, reasoning about performance requirements such as deadline misses, response time, and CPU usage requires the explicit modeling of time, which is one of the key characteristics of UML/MARTE (Section 2.2.2.3). For this reason, we provide a mapping of the abstractions in our conceptual model to UML/MARTE stereotypes and tagged values. This mapping shows the feasibility of extracting the abstractions required to support stress test cases generation from standard modeling languages.

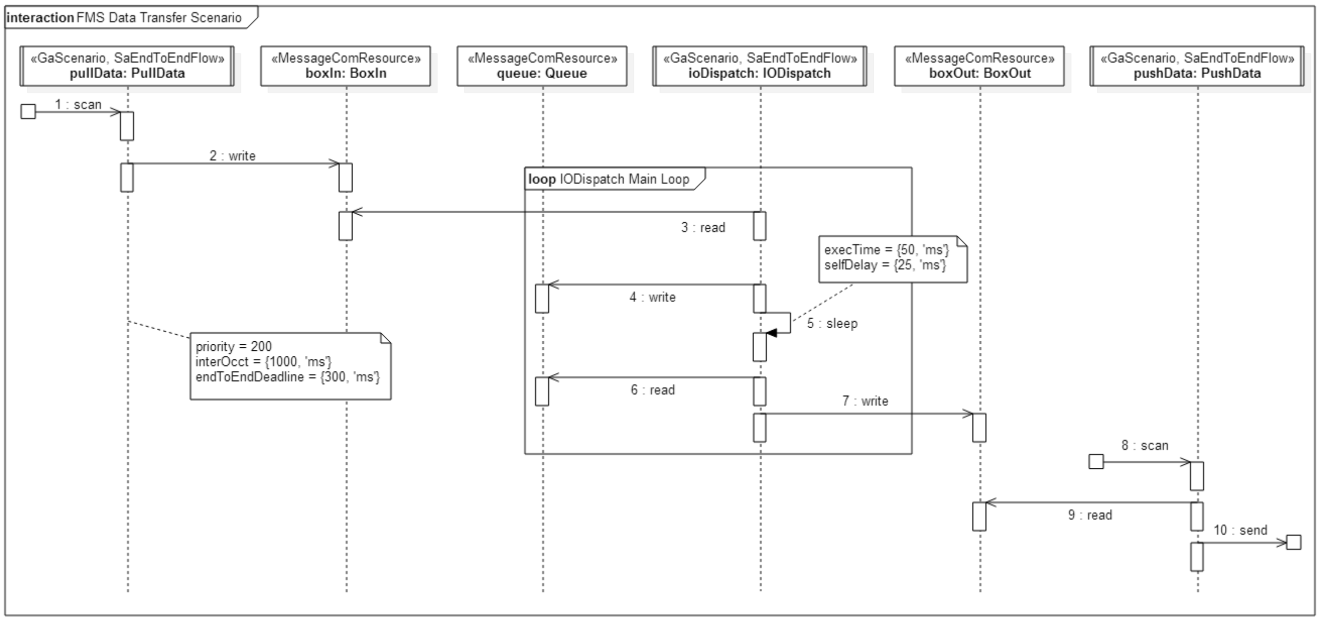

interaction FMS Data Transfer Scenario
«GaScenario, SaEndToEndFlow» pullData: PullData
«MessageComResource» boxIn: BoxIn
«MessageComResource» queue: Queue
«GaScenario, SaEndToEndFlow» ioDispatch: IODispatch
«MessageComResource» boxOut: BoxOut
«GaScenario, SaEndToEndFlow» pushData: PushData
1 : scan
2 : write
loop IODispatch Main Loop
3 : read
execTime = {50, 'ms'}
selfDelay = {25, 'ms'}
4 : write
5 : sleep
priority = 200
interOcct = {1000, 'ms'}
endToEndDeadline = {300, 'ms'}
6 : read
7 : write
8 : scan
9 : read
10 : send

Figure 5.3. A sequence diagram modeling the data transfer scenario described in Figure 3.6. The sequence diagram is stereotyped with UML/MARTE stereotypes and tagged values mapped to concepts in the conceptual model we defined.

Some of the abstractions in our conceptual model are already present in UML. Recall from Section 2.2.2.2 that each active object in a sequence diagram can be associated to a lifeline. In this way, execution specifications represent the activities in our conceptual model. Similarly, occurrence specifications represents sending and receiving of messages, and therefore can be used to describe the synchronous and asynchronous communication defined in our conceptual model. Figure 5.3 shows a sequence diagram capturing the data transfer scenario of the Fire and Gas Monitoring System (FMS) described in Section 3.2.2. Tasks in the driver application are active objects, while buffers are passive objects. Each activity within a task is depicted using an execution specification, i.e., as a box on the task lifeline that shows the interval of time that the task performs the activity. Therefore, *pullData* has two activities, *ioDispatch* has four, and *pushData* has three. Note that the order of activations on a task lifeline implies the temporal ordering between activities of that task. In sequence diagrams, a synchronous message between two activities is shown using an arrow with a filled head, while an asynchronous message is shown by an arrow with an open head. Synchronous communication is blocking and does not necessarily require a buffer, because the sending activity must wait until the receiving activity is ready to receive the message. On the other hand, asynchronous communications can use buffers. Recall from Section 3.1 that in the FMS, and hence in Figure 5.3, all communications are asynchronous and use buffers.

Even though UML sequence diagrams can already capture several concepts in a real-time application, other concepts defined in our conceptual model do not have appropriate counterparts in pure UML. Specifically, the schedulability concepts, and the timing and concurrency attributes of our conceptual model are captured by UML/MARTE. Recall from Section 2.2.2.3 that MARTE provides a Software Resource Modeling (SRM) package, that defines abstractions to model software resources, and communication between resources. Therefore, we map our notion of buffer to the *MessageComResource* stereotype, which is meant to represent artifacts for communicating messages among concurrent resources.

MARTE also provides a Generic Quantitative Analysis Modeling (GQAM) package, which is intended to provide a generic framework for collecting information required for performance and schedulability analysis. The domain model of this package includes two key abstractions that closely resemble our notions of task and activity, *Scenario* and *Step* respectively. A step is defined in the domain model of GQAM as a unit of execution, while a scenario is defined a sequence of steps. These two concepts are represented by the stereotypes «*GaStep*» and «*GaScenario*», which we map in our conceptual model to activities and tasks respectively. Note that these two stereotypes can be applied to a wide set of behavior-related elements in the UML metamodel, and in particular, to elements in sequence diagrams. In particular, «*GaScenario*» and «*GaStep*» inherit from both «*TimeModels::TimedProcessing*», which extends the UML metaclasses *Behavior*, *Message*, *Actions*, and «*GRM::Resource*», which extends *NamedElement*. Steps and Scenarios in MARTE also include a list of measures that are widely used for analyzing of real-time properties of embedded systems. We map attributes of tasks and activities in our conceptual model to the tagged values representing those measures. Specifically, we map *interOccTime*, the time interval between two successive occurrences of scenarios, to period, offset, minimum, and maximum inter-arrival times of task. We also map *execTime*, i.e., the execution time of a step, to duration of activities, and *selfDelay*, i.e., the time steps are delayed for execution, to activities delays and releases. These tagged values can be specified either as single values, or as bounds defining an interval. Note that «*GaScenario*» does not specify tagged values representing the concept of task deadline. Indeed, in MARTE, the concept of deadline is defined in the Schedulability Analysis Modeling (SAM) package, in particular through the domain class *EndToEndFlow*, and the associated stereotype «*SaEndToEndFlow*». For this reason, we also map «*SaEndToEndFlow*» to our notion of task, so that the task deadline is mapped to the tagged value *endToEndDeadline*. We point out one discrepancy in our mapping of tasks and activities. In MARTE, the concept of execution priority is defined for individual steps, rather than for scenarios. Nonetheless, at the implementation level, it is common to define priorities at task-level, rather than at activity-level. Indeed, our conceptual model reflects this fact by specifying priorities as task, rather than activity, attributes. To address this discrepancy, we assume in our mapping that steps within a scenario all have the same priority p, and hence the scenario has priority p.

Finally, the abstractions related to the computing platform in our conceptual model are not captured in sequence diagrams, but can be represented using MARTE stereotypes applied to class and deployment diagrams. Specifically, the Generic Resource Modeling (GRM) package defines the stereotypes «*Scheduler*» and «*SchedulingPolicy*», which are mapped to the corresponding entities in our conceptual model. Furthermore, we map processing units to «*ComputingResource*», and global clocks to «*LogicalClock*». In this way, we map the global clock time to the *timeBase* tagged value. Table 5.1 summarizes the mapping between entities in our conceptual model, and stereotypes in MARTE.

	Conceptual Model	**UML/MARTE**	
	Class/Attribute	Stereotype/Tagged Value	Sub-profile
Application	Task	«*GaScenario*»	*GQAM*
		«*SaEndToEndFlow*»	*SAM*
	Task::deadline	*SaEndToEndFlow::endToEndDeadline*	*SAM*
	Task::priority	*GaStep::priority* [1]	*GQAM*
	PeriodicTask::offset	*GaScenario::interOccT*	*GQAM*
	PeriodicTask::period	*GaScenario::interOccT*	*GQAM*
	AperiodicTask::maxIa	*GaScenario::interOccT*	*GQAM*
	AperiodicTask::minIa	*GaScenario::interOccT*	*GQAM*
	Activity	«*GaStep*»	*GQAM*
	Activity::delay	*GaStep::selfDelay*	*GQAM*
	Activity::duration	*GaStep::execTime*	*GQAM*
	Activity::release	*GaStep::selfDelay*	*GQAM*
	Buffer	«*MessageComResource*»	*SRM::SW_Interaction*
Platform	*Scheduler*	«*Scheduler*»	*GRM*
	Scheduler::policy	*Scheduler::schedPolicy*	*GRM*
	SchedulingPolicy	«*SchedPolicyType*»	*MARTE_Library::GRM_BasicTypes*
	ProcessingUnit	«*HwProcessor*»	*HRM::HW_Logical::HW_Computing*
	ProcessingUnit::nbCores	*HwProcessor::nbCores*	*HRM::HW_Logical::HW_Computing*
	GlobalClock	«*LogicalClock*»	*Time::TimeAccesses::Clocks*
	GlobalClock::time	*Clock::timeBase*	*Time::TimeAccesses::Clocks*

Table 5.1. Mapping of the entities in our conceptual model to UML/MARTE. *PeriodicTask*, *AperiodicTask* and *TriggeredTask* do not appear in the mapping because they inherit the stereotypes from their superclass *Task*.

5.3 Validation of the Conceptual Model in the Fire and Gas Monitoring System

The practical usefulness of our approach depends two main factors. First, we need to investigate whether the input to our approach, i.e., the system specification stereotyped with the subset of UML/MARTE we defined, can be provided with reasonable overhead. This first factor sums up to validating our conceptual model and its mapping to UML/MARTE in an industrial context, and is discussed in this section. Second, we also need to investigate whether the output of our approach can effectively be used to derive stress test cases that are likely to violate performance requirements. This second factor closely depends on the search strategies used to generate test cases, and is discussed in Section 6.2 and Section 7.2.

As discussed in Section 5.1, the information required for generating stress test cases is captured by the

[1]Note that, as explained above, MARTE defines the concept of priority at activity-level, rather than at task-level. For this reason, we assume that all activities in a task have the same priority. Therefore, the priority of a task is equal to the priority of its composing activities.

conceptual model we defined. To gather this information, we first built UML sequence diagrams for the FMS I/O drivers, starting by the existing design documents and implementation. Such sequence diagrams were iteratively validated and refined in collaboration with the lead engineer of the drivers in Kongsberg Maritime. We extracted the quantitative elements of our conceptual models, i.e., the concrete values for the tagged values, from design documents, source code, and performance profiling logs. Specifically, we extracted the values for priorities, deadlines, and periods of tasks from the certification design documents, and the drivers source code. Furthermore, we extracted the values for the activities duration from the performance profiling logs of the drivers. We created the sequence diagrams augmented with the timing information from the MARTE stereotypes over 8 days, involving approximately 25 man-hours of effort. This was considered worthwhile, as safety-critical I/O drivers have a long lifetime and are regularly certified. Finally, we obtained information on the computing platform from the RTOS configuration and hardware design documents. We finally remark that, the main rationale behind the mapping we provided in Table 5.1 is to allow engineers to develop and manipulate our input design notation with any modeling environment that supports UML/MARTE.

Chapter 6

Using Constraint Programming to Automate the Generation of Stress Test Cases

The main objective of the conceptual model and its mapping to UML/MARTE is to organize the input data for our approach, which automates the stress test case generation. Recall from Section 3.1 that we define a stress test case with respect to a performance requirement as a sequence of arrival times for aperiodic tasks which maximizes the chance to violate that requirement. In this section, we cast the generation of stress test cases as a search problem over the space of task arrival times, and we solve the search problem with Constraint Programming (CP). Specifically, we cast the search for arrival times as a Constrained Optimization Problem (COP) over the abstractions of our conceptual model (Section 6.1). The goal of the COP is finding arrival times for aperiodic tasks that maximize the likelihood of the RTES violating its performance requirements on task deadlines, response time and CPU usage. We refer to this strategy for generating stress test cases as *CP-based strategy*. When confusion with the programming paradigm can not arise, we also refer to the CP-based strategy as *CP*.

We assess the practical usefulness of our CP-based strategy in two steps. First, we validate the COP in the Fire and Gas Monitoring System (FMS) described in Section 3.2 (Section 6.2.1). This validation shows that the COP effectively identifies in a few minutes stress test cases that are predicted to violate the FMS requirements on deadline misses, response time, and CPU usage.

However, for practical use, test case generation has to accommodate time and budget constraints. For this reason, it is essential to investigate the trade-off between the time needed by a strategy to generate stress test cases, and their power for revealing deadline misses. Recall from Section 2.4.2.2 that a strategy based on Genetic Algorithms (GA) [Briand et al., 2006] has been proposed to support stress testing of task deadlines by searching for worst-case scenarios, and is therefore a natural comparison baseline. We refer to this strategy for generating stress test cases as *GA-based strategy*, or, when confusion with the metaheuristic can not arise, as *GA*. Therefore, the second step in validating CP consists in a systematic comparison with GA for the purpose of generating stress test cases for deadline misses. We designed a series of experiments in five subject systems from safety-critical domains, ranging in size and complexity (Section 6.2.2). The experiments show that, on average, GA is generally more *efficient*, i.e., faster in generating test cases, while CP is more *effective*, i.e., it generates test cases that are more likely to reveal deadline misses. Note that this result opens up the possibility to combine the two strategies in order to retain the advantages of both. An hybrid approach combining GA and CP, which aims at striking a profitable trade-off between efficiency and effectiveness, is discussed in Chapter 7.

6.1 A Constrained Optimization Problem to Automate the Generation of Stress Test Cases in Real-Time Embedded Systems

We address the problem of determining worst-case schedules of tasks with an approach inspired by the work done in Constraint Programming to solve traditional scheduling problems [Baptiste et al., 2001]. Specifically, we cast the search for real-time properties that characterize the worst-case schedules, namely arrival times for aperiodic tasks, as a Constraint Optimization Problem (COP). The key idea behind our formulation relies on five main points.

1. First, we model the system design, which is static and known prior to the analysis, as a set of constants (Section 6.1.1). The system design mainly consists of the tasks of the real-time application, their dependencies, period, duration, deadline, and priority.
2. Then, we model the system properties that depend on runtime behavior as a set of variables (Section 6.1.2). The main real-time properties are the number of task executions, the arrival times of aperiodic tasks, and the specific runtime schedule of the tasks.
3. We model the Real-Time Operating System (RTOS) scheduler as a set of constraints among such constants and variables (Section 6.1.3). Indeed, the real-time scheduler periodically checks for triggering signals of tasks and determines whether tasks are ready to be executed or need to be preempted. Constraints of our model are described in.
4. We model the performance requirement to be tested, i.e., task deadlines, response time, or CPU usage, as an objective function to be maximized (Section 6.1.4).
5. Finally, we encapsulate the logic behind the RTOS scheduler in an effective labeling strategy over the variables of the model (Section 6.1.5). By design, the scheduler tries to execute high priority tasks as soon as possible, potentially preempting tasks with lower priority. We exploit this behavior by proposing a labeling strategy for the variables related to tasks execution.

A graphical overview of our approach is shown in Figure 6.1. Our analysis is subject to two main assumptions:

1. The RTOS scheduler checks the running tasks for potential preemptions at regular and fixed intervals of time, called *time quanta*. Therefore, each time value in our problem is expressed as a multiple of a time quantum. Accordingly to the specification of the RTOS executing the FMS, we consider the length of ten milliseconds for time quanta.
2. The interval of time in which the scheduler switches context between tasks is negligible compared to a time quantum.

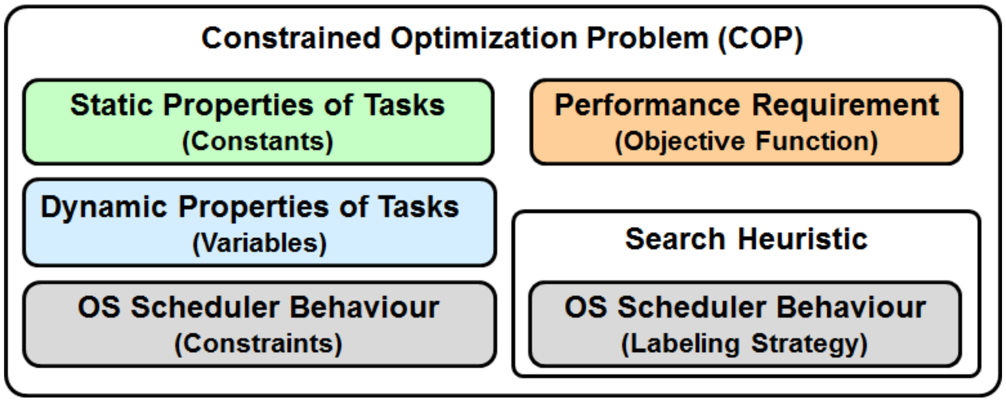


Figure 6.1. A graphical overview of the Constrained Optimization Model to generate stress test cases.

These two assumptions are reasonable in the context of RTES, as the scheduling rate of operating systems varies in the ranges of few milliseconds, while the time needed for context switching is usually in the order of nanoseconds [Singh, 2009]. These assumptions allow us to consider time as discrete, and model the COP as an Integer Program (IP) over finite domains. We implemented the COP in OPL, and solved it with IBM ILOG CPLEX CP OPTIMIZER. This choice was motivated by practical reasons, such as extensive documentation, strong supporting community, and its acknowledged efficiency to solve optimization problems. Despite the scheduling nature of our problem, we implemented our model as a traditional IP as opposed to using the scheduling features of OPL and CP OPTIMIZER. This is because we could not express a preemptive priority-driven scheduling behavior in an effective way that exploited the capabilities of the solver.

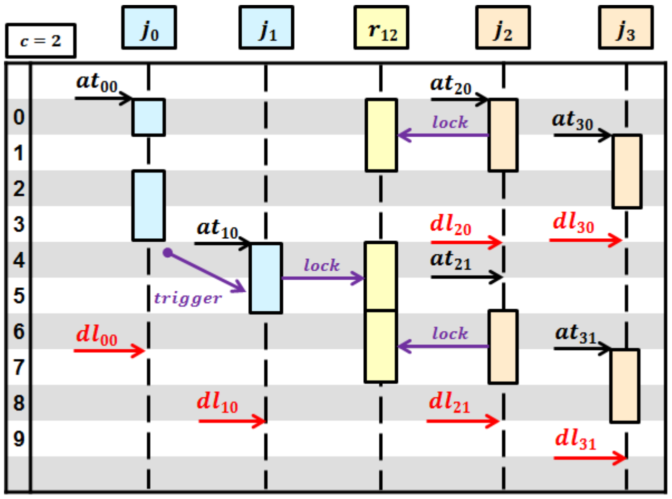


Figure 6.2. Real-time scheduling example of four tasks on a dual-core platform

The rest of this section details our constraint model using the example shown in Figure 6.2. This system features four tasks in increasing priority order, j_0 to j_3, running on a dual-core platform for 10 time units. j_0 and j_1 are executed once, while j_2 and j_3 are executed twice. The figure reports the arrival times and deadlines of the tasks, labeled by *at* and *dl* respectively, where the first index represents the task, and the second the task execution. In this example, j_0 is aperiodic, while j_2 and j_3 are periodic.

Note that task j_1 is triggered by j_0 upon termination, and that j_1 and j_2 share the resource r_{12} with exclusive access.

6.1.1 Constants

Constants are implemented as integers (*int*), integer ranges (*range*), tuples (*tuple*), sets of tuples (*setOf*) and integer expressions. Integers values are defined as external data.

Observation Interval. *We define T as an integer interval of length tq, i.e.,* $T \overset{def}{=} [0, tq-1]$.

T represents the time interval during which we observe the system behavior. Note that T is an integer interval, as a consequence that time is discretized in our analysis. Therefore, each time value $t \in T$ is a time quantum. In Figure 6.2, $tq = 10$ and $T = [0, 9]$.

Number of platform cores. *We define c as the number of cores in the execution platform.*

c represents the maximum number of tasks that can be executed in parallel. In Figure 6.2, $c = 2$, as at most two tasks are allowed to run in parallel.

Set of tasks. *We define J as the set of tasks of the system. We define* J_p, J_a, *and* J_g *as the set of periodic, aperiodic, and triggered system tasks, respectively.*

Each task $j \in J$ has a set of *static* properties, defined as constants, and a set of *dynamic* properties, defined as variables. Note that J_p, J_a, and J_g define a partition over J. We assume that OS tasks have lower priority than system tasks and can be preempted at any time, and hence, can be abstracted away in our analysis. Each task j is implemented as an OPL tuple named *Task*, whose fields are the following non-relation constants. J is implemented as an OPL tuple set, while J_p, J_a, and J_g are OPL generic sets derived from J. In Figure 6.2, $J = \{j_0, j_1, j_2, j_3\}$, $J_a = \{j_0\}$, $J_p = \{j_2, j_3\}$, and $J_g = \{j_1\}$.

Priority of a task. *We define* $pr(j)$ *as the priority of task j. For simplicity, we define the set* HP_j *of tasks having higher or equal priority than j:* $HP_j \overset{def}{=} \{j_1 \in J \mid j \neq j_1 \wedge pr(j_1) \geq pr(j)\}$.

In Figure 6.2, $pr(j_0) = 0$, $pr(j_1) = 1$, $pr(j_2) = 2$, and $pr(j_3) = 3$.

Period of a task. *We define* $pe(j)$ *as the period of task j.*

$pe(j)$ is only defined if j is periodic. In Figure 6.2, $pe(j_2) = 5$ and $pe(j_3) = 6$.

Offset of a task. *We define* $of(j)$ *as the offset of task j, i.e., the time, counted from the beginning of T, after which the first period of task j begins.*

$of(j)$ is only defined if j is periodic. In Figure 6.2, $of(j_2) = 0$ and $of(j_3) = 1$.

Delay of a task. *We define* $dy(j)$ *as the delay of task j, i.e., the time, that has to occur between two executions of j.*

In Figure 6.2, $dy(j_2) = 3$.

Release of a task. *We define $re(j)$ as the release of task j, i.e., the time that j has to wait after its arrival before starting to execute.*

In Figure 6.2, all tasks have release 0.

Minimum and maximum inter-arrival times of a task. *We define $mn(j)$ and $mx(j)$ as the minimum and maximum inter-arrival times of task j, respectively, i.e., the minimum and maximum time separating two consecutive arrival times of j.*

$mn(j)$ and $mx(j)$ are only defined if j is aperiodic since for all periodic tasks j, $mn(j) = mx(j) = pe(j)$ trivially holds. In Figure 6.2, we assumed $mn(j_0) = 5$ and $mx(j_0) = 10$.

Duration of a task. *We define $dr(j)$ as the estimated Worst Case Execution Time (WCET) of task j. For simplicity, we define the integer interval P_j of* execution slots *as $P_j \overset{\text{def}}{=} \big[0,\ dr(j)-1\big]$.*

Since OPL does not support indexed ranges, P_j is implemented as a single range $P \overset{\text{def}}{=} [0, \max\limits_{j\in J} dr(j)-1]$. This definition entails that $\forall j \in J \cdot P_j \subseteq P$. The iteration through values in P_j is emulated with a logic implication. Indeed, the following properties hold for every logic predicate C and arithmetic expression E.

$$\forall p \in P_j \cdot C(p) \iff \forall p \in P \cdot p < dr(j) \implies C(p) \tag{6.1}$$

$$\sum_{p\in P_j} E(p) = \sum_{p\in P} \big(p < dr(j)\big) \cdot E(p) \tag{6.2}$$

Note that in Equation (6.2) $\big(p < dr(j)\big)$ is a boolean expression that is true if $p < dr(j)$, and false otherwise. For the rest of this paper, equalities and inequalities written within parentheses represent boolean expressions that evaluate to the integer 1 if true, and to the integer 0 if false. This is also the default behavior in CP OPTIMIZER. In Figure 6.2, $dr(j_0) = 3$ and $P_{j_0} = [0,1,2]$.

Deadline of a task. *We define $dl(j)$ as the time, with respect to its arrival time, before which task j should terminate.*

In Figure 6.2, $dl(j_0) = 7$, $dl(j_1) = 6$, $dl(j_2) = 4$, and $dl(j_3) = 3$.

Triggering relation between tasks. *We define $tg(j_1, j_2)$ as a binary relation between tasks j_1 and j_2 that holds if the event triggering j_2 occurs when j_1 finishes its execution. We define the sets TS_j and ST_j of tasks triggered by and triggering j, respectively.*

$$TS_j \overset{\text{def}}{=} \{j_1 \in J \mid tg(j, j_1)\} \qquad ST_j \overset{\text{def}}{=} \{j_1 \in J \mid tg(j_1, j)\}$$

The relation tg is defined as irreflexive and antisymmetric. tg is implemented as an OPL tuple with two fields, the first being the task triggering, and the second being the task triggered. In Figure 6.2, $tg(j_0, j_1)$ holds.

Dependency relation between tasks. *We define $de(j_1, j_2)$ as a binary relation between tasks j_1 and j_2 that holds if there exists a computational resource r such that j_1 and j_2 access r during their execution* *in an exclusive way. We define the set DS_j of tasks depending on j.*

$$DS_j \overset{\text{def}}{=} \{j_1 \in J \mid j \neq j_1 \wedge de(j_1, j)\} \tag{6.3}$$

The relation *de* is defined as reflexive and symmetric. This definition implies that j_1 and j_2 cannot be executed in parallel nor can preempt each other, but one can execute only after the other has released the lock on the resource. *de* is implemented as an OPL tuple with two fields, each being one of the task depending on the other. In Figure 6.2, $de(j_1, j_2)$ holds.

6.1.2 Variables

Independent variables in our model are implemented as OPL finite domain variables (*dvar int*). Dependent variables are implemented as OPL variable expressions (*dexpr int*) defined through equality constraints. The first three variables described hereafter, namely the number of task executions, their arrival times, and active sets, are independent variables. The remaining variables described in this section are all dependent.

Number of task executions. *We define $te(j)$ as the number of times task j is executed within T. For simplicity, we define the integer interval K_j of task executions for the task j as* $K_j \overset{\text{def}}{=} [0,\ te(j)-1]$.

Note that we refer to the kth execution of task j as the couple (j,k). We assume the minimum and maximum inter-arrival times bound the number of executions of an aperiodic task. This means that, for aperiodic tasks, $te(j)$ is defined as a variable with domain $\left[\left\lfloor \frac{tq}{mx(j)} \right\rfloor,\ \left\lfloor \frac{tq}{mn(j)} \right\rfloor\right]$. Similarly, we assume that offset and period statically determine the number of executions of periodic tasks so that $te(j) = \left\lfloor \frac{tq-of(j)}{pe(j)} \right\rfloor$. Therefore, the number of task executions of periodic tasks is constant, rather than variable. However, we do not formally distinguish it from the number of task execution for aperiodic tasks. *te* is implemented as an integer array ranging over J_p if the task is periodic (or ranging over J_g if triggered by a periodic task), and as an integer variables array ranging over J_a if the task is aperiodic (or ranging over J_g if triggered by an aperiodic task). Since OPL does not support ranges with variable bounds, K_j is implemented as a single constant range K.

$$K \overset{\text{def}}{=} \left[0,\ \max\left(\max_{j\in J_p}\left\lfloor \frac{tq-of(j)}{pe(j)} \right\rfloor, \max_{j\in J_a}\left\lfloor \frac{tq}{mn(j)} \right\rfloor\right)\right]$$

Note that K is defined as a range from 0 to the largest upper-bound for task executions of periodic and aperiodic tasks. This definition entails that $\forall j \in J \cdot K_j \subseteq K$. The iteration through values in K_j is performed in a similar way as the case of P_j, thanks to the following properties for each logic predicate C and arithmetic expression E.

$$\forall k \in K_j \cdot C(k) \iff \forall k \in K \cdot k < te(j) \implies C(k) \tag{6.4}$$

$$\sum_{k\in K_j} E(k) = \sum_{k\in K} \Big(k < te(j)\Big) \cdot E(k) \tag{6.5}$$

In Figure 6.2, $te(j_0) = 1$, $te(j_3) = 2$, $K_{j_1} = [0]$, and $K_{j_2} = [0,1]$.

Arrival time of a task execution. *We define $at(j,k)$ as the time when an event notifies the RTOS that task j should be executed for the k^{th} time.*

We say that j *arrives* for the k^{th} time at time t iff $at(j,k) = t$. When the specific execution k of j is understandable from the context, we simply say that j arrives at time t. In our analysis, we assume that the arrival time of periodic tasks is constant: $\forall j \in J_p,\ k \in K_j \cdot at(j,k) = of(j) + k \cdot pe(j)$. Similarly to the case of *te*, we do not formally distinguish the arrival times of periodic and aperiodic tasks. *at* has domain T for aperiodic tasks. In Figure 6.2, $at(j_0,0) = 0$ and $at(j_2,1) = 5$.

Active set of task executions. *We define $ac(j,k,p)$ as the p^{th} time quantum in T in which task j is running for the k^{th} execution. We also define $A_{j,k}$ as the integer vector of time quanta where j is executing for the k^{th} time, the vector A_j of time quanta where j is executing, and the vector A of time quanta where tasks are executing.*

$$A_{j,k} \stackrel{\text{def}}{=} [ac(j,k,p) \mid p \in P_j] \qquad A_j \stackrel{\text{def}}{=} [A_{j,k} \mid k \in K_j] \qquad A \stackrel{\text{def}}{=} [A_j \mid j \in J]$$

Note that A_j and A are defined as vectors of vectors. Also note that we refer to both the set of all *ac* variables, and to A, as the *schedule* produced by the arrival times of the tasks in J. *ac* variables have domain T. In Figure 6.2, $ac(j_0,0,0) = 0$, $ac(j_0,0,1) = 2$, $A_{j_0,0} = [1,2,4]$, $A_{j_0} = \Big[[1,2,3]\Big]$, and
$A = \Bigg[\Big[[1,2,3]\Big], \Big[[4,5]\Big], \Big[[0,1],[6,7]\Big], \Big[[1,2],[7,8]\Big]\Bigg]$.

Preempted set of task executions. *We define $pm(j,k,p)$ as the number of time quanta for which the k^{th} execution of task j is preempted for the p^{th} time.*

$$pm(j,k,p) \stackrel{\text{def}}{=} ac(j,k,p) - ac(j,k,p-1) - 1$$

pm is only defined for $p > 0$. In Figure 6.2, $pm(j_0,0,1) = 1$, and $pm(j_0,0,2) = 0$.

Start and end times of task executions. *We define $st(j,k)$ and $en(j,k)$ as the first and the one after the last time quantum in which task j is executing for the k^{th} time.*

$$st(j,k) \stackrel{\text{def}}{=} ac(j,k,0) \qquad en(j,k) \stackrel{\text{def}}{=} ac\Big(j,k,dr(j)-1\Big) + 1$$

We say that j *starts* or *ends* for the k^{th} time at time t iff $st(j,k) = t$ or $en(j,k) = t-1$, respectively. In Figure 6.2, $st(j_0,0) = 0$ and $en(j_1,0) = 6$.

Waiting time of task executions. *We define $wt(j,k)$ as the time that j waits after its arrival time before starting its k^{th} execution.*

$$wt(j,k) \stackrel{\text{def}}{=} st(j,k) - at(j,k)$$

In Figure 6.2, $wt(j_0,0) = 0$, and $wt(j_2,1) = 1$.

Deadline of task execution. *We define $ed(j,k)$ as the absolute deadline of the k^{th} execution of j, i.e., the time, with respect to the beginning of T, before which j should terminate to meet its deadline.*

$$ed(j,k) \overset{def}{=} at(j,k) + dl(j) - 1$$

ed is implemented as two-dimensional array of integer variable expressions ranging over the set J and the range K. In Figure 6.2, $ed(j_0,0) = 6$, and $ed(j_1,0) = 8$.

Deadline miss of task execution. *We define $dm(j,k)$ be the amount of time by which j missed its deadline during its k^{th} execution.*

$$dm(j,k) \overset{def}{=} en(j,k) - ed(j,k) - 1$$

dm is implemented as two-dimensional array of integer variable expressions ranging over the set J and the range K. In Figure 6.2, $dm(j_0,0) = -3$.

Blocking task execution time quantum. *We define $bl(j,k,j_1,k_1,p_1)$ as a boolean variable that is true if in the interval $\Big[at(j,k), st(j,k)\Big)$ the task execution (j_1,k_1) is active at the time slot p_1:*

$$bl(j,k,j_1,k_1,p_1) \overset{def}{=} at(j,k) \leq ac(j_1,k_1,p_1) < st(j,k)$$

In Figure 6.2, $bl(j_2,1,j_1,0,1) = true$, since $(j_2,0)$ waits at $t = 5$ for the last time quantum of $(j_1,0)$ before starting.

Higher priority active tasks. *We define $ha(j,k)$ as the number of time quanta in the interval $\Big[at(j,k), st(j,k)\Big)$ where exactly c tasks having higher priority of j and not depending on j are active. Consider the summation indexes j_1, k_1, p_1 defined over the sets $HP_j \setminus DS_j$, K_{j_1}, and P_{j_1} respectively, and the summation indexes j_2, k_2, and p_2 defined over the sets $HP_j \setminus DS_j$, K_{j_2}, and P_{j_2}, respectively.*

$$ha(j,k) \overset{def}{=} \sum_{j_1,k_1,p_1} \left(bl(j,k,j_1,k_1,p_1) \wedge \left(\Big(\sum_{j_2,k_2,p_2} bl(j,k,j_2,k_2,p_2) \Big) = c \right) \right)$$

Note that for the definition of $ha(j,k)$, it is important that HP_j also includes tasks with equal priority than j. This is because, in the RTOS scheduling policy we consider, tasks can only preempt tasks with strictly lower priority. In Figure 6.2, $ha(j,k) = 0$ for all task executions (j,k), since in no case there are two tasks active when a task is waiting.

Dependent active tasks. *We define $da(j,k)$ as the number of time quanta in the interval $\Big[at(j,k), st(j,k)\Big)$ where task executions depending on j is active. Consider the summation indexes j_1, k_1, p_1 defined over the sets DS_j, K_{j_1}, and P_{j_1}, respectively.*

$$da(j,k) \overset{def}{=} \sum_{j_1,k_1,p_1} bl(j,k,j_1,k_1,p_1)$$

In Figure 6.2, $da(j_2,1)=1$, because j_1 is active for the time quantum $t=5$ between the arrival and the start of j_2.

Dependent preempted tasks. *We define $dp(j,k)$ as the number of time quanta in the interval $\big[at(j,k),st(j,k)\big)$ where task executions depending on j have been preempted. Consider the summation indexes j_1, k_1, p_1 defined over the sets DS_j, K_{j_1}, and P_{j_1}, respectively.*

$$dp(j,k) \overset{\text{def}}{=} \sum_{j_1,k_1,p_1} pm(j_1,k_1,p_1)\cdot bl(j,k,j_1,k_1,p_1)$$

In Figure 6.2, $dp(j,k)=0$ for all task executions (j,k), since there are no dependent task preempted that block the execution of any task.

System load. *We define $ld(t)$ as the load of the system at time t, i.e., the number of tasks active at time t. Consider the summation indexes j, k, p defined over the sets J, K_j, and P_j, respectively.*

$$ld(t) \overset{\text{def}}{=} \sum_{j,k,p} \Big(ac(j,k,p)=t\Big)$$

In Figure 6.2, $ld(0)=2$, and $ld(3)=1$.

6.1.3 Constraints

We define five groups of constraints related to different aspects of the RTOS.

Well-formedness Constraints. *Well-formedness constraints specify relations among variables that directly follow from their definition in the schedulability theory.*

Constraint WF1. *Each task execution starts after its arrival and release time, and ends after the task duration.*

$$\forall j \in J,\ k \in K_j \cdot at(j,k)+re(j) \le st(j,k) \le en(j,k)-dr(j) \tag{WF1}$$

Constraint WF2. *Consecutive executions of the same task are separated by task delays*

$$\forall j \in J,\ k \in K_j \setminus \{0\} \cdot en(j,k-1)+dy(j) \le st(j,k) \tag{WF2}$$

Constraint WF3. *Arrival times of aperiodic tasks are separated by their minimum and maximum inter-arrival times.*

$$\forall j \in J_a,\ k \in K_j \setminus \{0\} \cdot at(j,k-1)+mn(j) \le at(j,k) \le at(j,k-1)+mx(j) \tag{WF3}$$

Constraint WF4. *The time indexes $p \in P_j$ define an order over the active time quanta of tasks.*

$$\forall j \in J,\ k \in K_j,\ p \in P_j \setminus \{0\} \ \cdot\ ac(j,k,p-1) < ac(j,k,p) \tag{WF4}$$

Temporal Ordering Constraints. *Temporal Ordering Constraints specify the relative ordering of tasks basing on their dependency and triggering relations.*

Constraint TO1. *Each triggered task is executed the same number of times of its triggering task.*

$$\forall j_1 \in J,\ j_2 \in TS_j \ \cdot\ te(j_1) = te(j_2) \tag{TO1}$$

Constraint TO2. *Each triggered task execution arrives when its triggering task execution ends.*

$$\forall j_1 \in J,\ k \in K_{j_1}\ j_2 \in TS_j \ \cdot\ en(j_1,k) = at(j_2,k) \tag{TO2}$$

Constraint TO3. *Executions of dependent tasks cannot overlap, i.e., each task can only start after the one it depends on has ended.*

$$\begin{aligned}\forall j_1 \in J,\ k_1 \in K_{j_1}\ j_2 \in DS_j,\ k_2 \in K_{j_2} \cdot en(j_1,k_1) \leq st(j_2,k_2) \vee \\ en(j_2,k_2) \leq st(j_1,k_1)\end{aligned} \tag{TO3}$$

Constraint TO4. *If two tasks that depend on each other arrive at the same time, the higher priority task executes first.*

$$\begin{gathered}\forall j_1 \in J,\ k_1 \in K_{j_1},\ j_2 \in \Big(DS_j \cap (J \setminus HP_j)\Big),\ k_2 \in K_{j_2} \cdot \\ at(j_1,k_1) = at(j_2,k_2) \implies st(j_1,k_1) < st(j_2,k_2)\end{gathered} \tag{TO4}$$

Multi-core Constraint. *The Multi-core Constraint captures the specification of the number c of cores of the computing platform, and stating that no more than c tasks are allowed to be active in parallel at any time. The constraint specifies that the system load should be less than the number of cores at any time.*

$$\forall t \in T \ \cdot\ ld(t) \leq c \tag{MC}$$

Note that, when $c = 1$, MC is equivalent to an *alldifferent* constraint over *ac*.

Preemption Constraint. *The Preemption Constraint captures the priority-driven preemptive scheduling of the RTOS, and stating that each task should be preempted when a higher priority task is ready to be executed and no cores are available. The constraints specifies that the number of time quanta where a task execution is preempted times c is equal to the number of time quanta where higher priority tasks are active. Consider the summation indexes j_1, k_1, and p_1 defined over the sets HP_j, K_{j_1}, and P_{j_1} respectively.*

$$\begin{aligned}&\forall j \in J,\ k \in K_j,\ p \in P_j \ \cdot \\ &pm(j,k,p) \cdot c = \sum_{j_1,k_1,p_1} \Big(ac(j,k,p-1) < ac(j_1,k_1,p_1) < ac(j,k,p)\Big)\end{aligned} \tag{P}$$

Scheduling Efficiency Constraint. *The Scheduling Efficiency Constraint ensures that there is no unnecessary task preemption, and that tasks are executed as soon as possible. The constraint specifies that, for each time quanta in which a task execution (j,k) is waiting, there should be either (1) exactly c tasks with higher priority that do not depend on j active, or (2) one task execution dependent on j that is active, or (3) one task execution dependent on j that is preempted.*

$$\forall j \in J,\ k \in K_j \ \cdot\ wt(j,k) = ha(j,k) + da(j,k) + dp(j,k) \tag{SE}$$

6.1.4 Objective Functions

We formalized three objective functions, each modeling one performance requirement, and each meant to be maximized in a separate constraint model having the same constants, variables, and constraints. In this way, solutions to each of the three constraint models characterize worst-case scenarios for the requirement modeled by the function.

Task Deadline Misses Function. *We define F_{DM} as the function that models the performance requirement involving task deadlines.*

$$F_{DM} = \sum_{j \in J,\ k \in K_j} 2^{\,dm(j,k)}$$

As explained at the beginning of this chapter, the goal of our approach is to find values for the arrival times of aperiodic tasks that maximize the likelihood of violating performance requirements, in particular deadline misses. We formalized this concept through an objective function of whose value captures how arrival times compare in terms of their likelihood of triggering deadline misses. We first identify a set of characteristics the function should meet:

- *No deadline miss is overshadowed.* In safety-critical real-time systems even a single deadline miss could lead the system to a fail state. Thus, a good function should not allow task executions which meet their deadline to overshadow deadline misses.
- *The more deadline misses, the higher the value.* Intuitively, the function value should take into account the number of deadline misses among task executions. Even if a system could recover from a scenario where a task misses its deadline in a single execution, recovering from several deadline misses might be harder.
- *The larger the deadline misses, the higher the value.* Our analysis is based on WCET estimates (*duration*) for the system tasks. Such estimates could be over-pessimistic, and our approach could compute a test case identifying a deadline miss that does not happen when actually testing the system. However, the closest to its deadline a task is in our analysis, the more likely it is to miss a deadline in a real scenario. Such concept is captured by the quantity defined as *deadline_miss*: the larger its value, the closer the task completion time to its deadline, with possibly the task missing its deadline. Hence, we expect a good function to prioritize scenarios where a larger deadline miss is identified.

Having considered the criteria above, we adopted a modified version of the function defined by Briand et al. [Briand et al., 2006]:

$$f(j) = \sum_{k \in K_j} 2^{\,dm(j,k)}$$

Note that f is defined for a given task j. F_{DM} is an alternative formulation of f which instead takes into account all tasks is given by the sum of f for each task in the system:

$$F_{DM} = \sum_{j \in J} f(j)$$

Also note that the purpose of $f(j)$ is to identify deadline miss scenarios for a single critical task j, since it has larger values when large deadline misses occur in j. On the other hand, F_{DM} has larger values when more deadline misses on several tasks occur, aiming at identifying scenarios stressing the whole system rather than a single task. Given that we use our subject systems for the purpose of experimental evaluation and comparison, there is no clear guidance on how to choose a specific target task j for each case. For this reason, we model the performance requirement involving task deadlines with F_{DM}. Recall from Section 6.1.2 that, $dm(j,k)$ is positive if task j misses its deadline during its k^{th} execution, and negative otherwise. This means that large negative values stand for j ending long before its deadline. On the other hand, positive values stand for j failing to end before its deadline, thus missing it. The exponential shape of the function favors executions with large deadline misses, thus avoiding them being overshadowed by other executions.

Response Time Function. *We define F_{RT} as the function that models the system response time.*

$$F_{RT} = \left(\max_{j \in J,\, k \in K_j} en(j,k) \right) - \left(\min_{j \in J,\, k \in K_j} at(j,k) \right)$$

F_{RT} measures the total length in time quanta of the schedule, starting from when the first task arrives, up to when the last ends. This function is also known in traditional scheduling as *makespan*.

CPU Usage Function. *We define F_{CU} as the function that models the system CPU usage.*

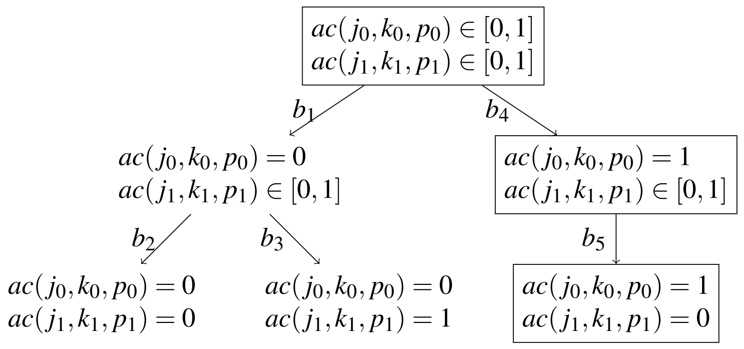
$$F_{CU} = \frac{\sum_{t \in T} \left(ld(t) > 0 \right)}{tq}$$

F_{CU} measures the average CPU usage of the system over T, by counting all the time quanta where at least one task is active, i.e., where the system load is greater than 0.

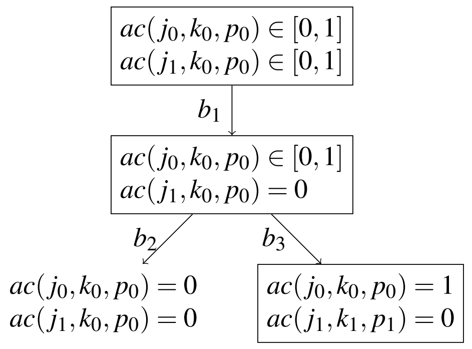
6.1.5 Search Heuristic

We defined a search heuristic that refines the branching process of the CP OPTIMIZER solving algorithm. The heuristic specifies that the solver should mimic the behavior of a RTOS by first trying to schedule tasks with higher priority. This is done by choosing the *ac* variables to branch on by decreasing priority, and then by assigning their time values in increasing order. For example, consider a system where $c = 1$, $j_0, j_1 \in J$, $pr(j_1) > pr(j_0)$. Suppose that, for given k_0, p_0, k_1, j_1 the filtering algorithm reduced the domains of the *ac* variables to the set $[0,1]$. Figure 6.3.1 shows the branching tree in case the solver runs with default settings.

In the root node, the *ac* variables have domain $[0,1]$. The solver then tries the first variable assignment in the branch b_1, stating that j_0 is executing at time 0. Then, the solver tries the second assignment in the branch b_2, stating that j_1 is executing at time 0. This variable assignment violates the multi-core constraint MC since both j_0 and j_1 are executing at the same time. Therefore, the solver prunes the node, backtracks to the father node, and tries the assignment in b_3 where j_1 is executing at time 1. This assignment violates the preemptive scheduling constraint P, since j_1 has higher priority, but j_0 is running instead. Only after backtracking up to the root node, the solver tries the assignments in b_4 and b_5 which do not violate any constraint. Note that several other branching steps might have been necessary if $ac(j_1,k_1,p_1)$ had a larger domain.



(6.3.1) Branch and bound without our heuristic



(6.3.2) Branch and bound with our heuristic

Figure 6.3. Branch and bound backtracking without and with our search heuristic. The nodes with a solid border are the ones leading to a feasible solution.

Consider Figure 6.3.2, where the solver has been instructed to first branch by assigning the smallest value in its domain to the *ac* variable associated with the highest priority task. In this case, the solver tries the first assignment $ac(j_1,k_1,p_1) = 0$ in the branch b_1. Then, it tries the second assignment in the branch b_2, that violates MC. However, the third assignment in b_3 does not violate any constraint, making the solver perform only one backtracking step.

The semantics of this heuristic, i.e., highest priority tasks should be scheduled first, is the same as the semantics of the RTOS scheduler, which in turn is captured by preemptive scheduling constraint. By using this concept in the branching process, the solver is less likely to assign values for *ac* that violate the preemptive scheduling constraint, and thus finds solutions faster. We implemented the search heuristic within a stand-alone application that solves the OPL model using the .NET CONCERT library to interface with the CP OPTIMIZER. Experimentation with our search heuristic showed a significant decrease in the time needed by the solver to find solutions.

6.2 Validation of the CP-based Strategy for Stress Test Cases Generation

We first assessed the practical usefulness of our CP-based strategy in the Fire and Gas Monitoring System (FMS) described in Section 3.2. Recall from Section 6.2.1 that the FMS is a RTES whose main goal is to monitor potential gas leaks and fires in offshore platforms, and activate countermeasures in case hazardous events are detected. Currently, KM engineers spend several days simulating the behavior of the FMS and monitoring its performance requirements. We expect that, by following our systematic CP-based approach for stress testing, they can effectively derive stress test cases to produce satisfactory evidence that no safety risks are posed by violating performance requirements at runtime. We note that our methodology draws on context factors (Section 3.2) that need to be ascertained prior to application. While the generalizability of these factors needs to be further studied, we have found them to be commonplace in many industry sectors relying on RTES. Furthermore, we note how casting the worst-case scenario analysis as a search problem relies on modeling the property to stress test as an objective function to be maximized. This is a flexible design when it comes to adapting the constraint model to test different performance requirements. Indeed, in such cases, it is only needed to consider a different objective function modeling another performance requirement. Moreover, the final users of our approach, i.e., software testers and engineers, do not need to be aware of the mathematical details of the constraint model, as they can simply use our methodology as a black box test cases generator. Overall, the validation of our CP-based strategy shows that the COP effectively identifies in a few minutes stress test cases that are predicted to violate the FMS requirements on deadline misses, response time, and CPU usage.

However, for practical use, test case generation has to accommodate time and budget constraints. For this reason, it is essential to investigate the trade-off between the time needed by a strategy to generate stress test cases, and their power for revealing deadline misses. Recall from Section 2.4.2.2 that a strategy based on Genetic Algorithms (GA) [Briand et al., 2006] has been proposed to support stress testing of task deadlines by searching for worst-case scenarios, and is therefore a natural comparison baseline. We refer to this strategy for generating stress test cases as *GA-based strategy*. When confusion with the metaheuristic can not arise, we also refer to the GA-based strategy as *GA*. After validating CP in the FMS, we compared CP with GA for the purpose of generating stress test cases for deadline misses. To do so, we designed a series of experiments in five subject systems from safety-critical domains, ranging in size and complexity (Section 6.2.2). The experiments show that, on average, GA is generally more *efficient*, i.e., faster in generating test cases, while CP is more *effective*, i.e., it generates test cases that are more likely to reveal deadline misses. Note that this result opens up the possibility to combine the two strategies in order to retain the advantages of both. An hybrid approach combining GA and CP which aims at striking a profitable trade-off between efficiency and effectiveness is discussed in Chapter 7.

6.2.1 Validation of CP in the Fire and Gas Monitoring System

Recall from Section 3.2 that the work reported in this thesis originates from the interaction over the years with Kongsberg Maritime (KM), a leading company in the maritime and energy field. KM has pressing needs to improve its practices related to safety certification, and this involves improving the validation of performance requirements. Therefore, we proposed, along with the approach in Chapter 5, the CP-based strategy described in this chapter to provide support for systematic performance testing.

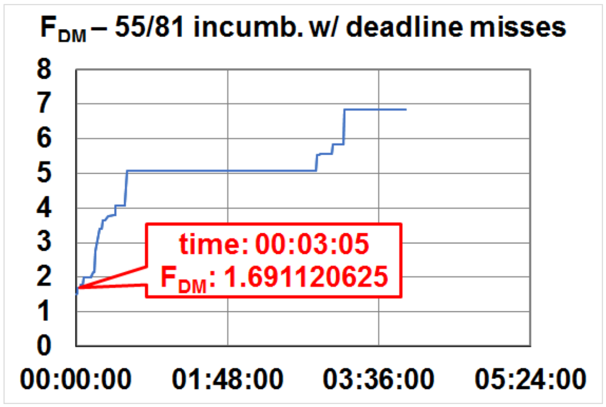
The main goal of evaluating CP for stress testing is to investigate whether engineers can use the solutions of our Constrained Optimization Problem (COP), i.e., the values for the *at* variables (Section 6.1.2), to derive stress test cases for different performance requirements. Indeed, recall from Section 3.1 that we characterize stress test cases by arrival times of aperiodic tasks in the FMS drivers. We performed an experiment with the FMS drivers with an observation interval T of five seconds, assuming time quanta of 10 ms. We run our OPL model for three times on a single AMAZON EC2 M2.XLARGE instance[1]. Each run maximized one objective function defined in Section 6.1.4, and had a duration of five hours. Figure 6.4 shows the feasible solutions with the best objective value that were found within five hours. Consistent with the terminology used in Integer Programming, we refer to these solutions as *incumbents* [Atamtürk and Savelsbergh, 2005]. In each graph, the x-axis reports the incumbent computation times in the format *hh:mm:ss*, and the y-axis reports the corresponding objective value. The constraint problems had almost 600 variables and more than one million constraints, using up to 10 GB RAM during resolution.

Since software testing has to accommodate time and budget constraints, we also investigated the trade-off between the time needed to generate test cases, and their power for revealing violations of performance requirements. For this reason, we recorded the computation times of the first incumbents predicted to violate the three performance requirements as expressed in Section 3.2. The run optimizing F_{DM} is shown in Figure 6.4.1. The solver found 55 out of a total of 81 incumbents with at least one deadline miss in their schedule; the first of such solutions was found after three minutes. The solution yielding the best value for F_{DM} produced a schedule where the *PushData* task missed its deadline by 10 ms in three executions over T. Figure 6.4.2 shows the results for the run optimizing F_{RT}. The solver found 18 out of 19 incumbents with response time higher than one second; the first of such solutions was found after two minutes. The best solution with respect to F_{RT} produced a schedule where the response time of the system was 1.2 seconds. Finally, the solutions found by optimizing F_{CU} are shown in Figure 6.4.3. The solver found 16 out of 20 incumbents with CPU usage above 20%; the first of such solutions was found after four minutes. The solution with the highest value for F_{CU} produced a schedule where the CPU usage of the system was 32%. In all of the three runs the solver terminated after the time budget of five hours, without completing the search with proof of optimality. However, for each objective function, the solver was able to find, within few minutes, solutions that are candidates to stress test the system as they may lead to requirements violations. Note that these solutions can be used to start testing the system while the search continues, because the highest the objective value, the more likely the solutions are to push the system to violating its performance requirements.

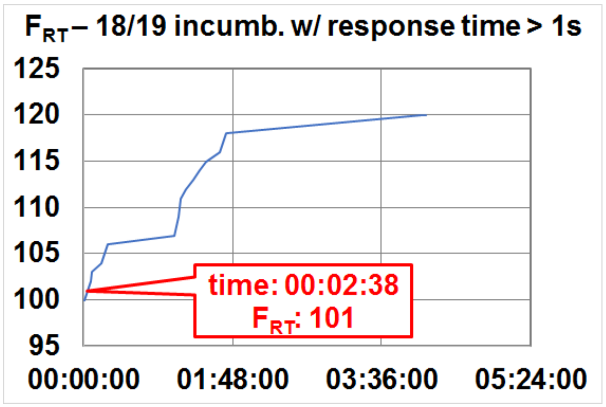
6.2.2 Validation of CP in Five Systems from Safety-critical Domains

After the initial validation of our CP-based strategy in the FMS, we investigated the overall performance of CP for the purpose of generating stress test cases that break task deadlines. Recall from Section 2.4.2.2 that a strategy based on Genetic Algorithms (GA) [Briand et al., 2006] has been recently proposed to

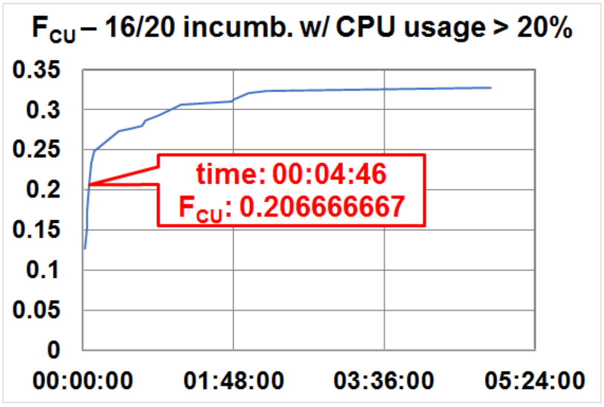
[1] `http://aws.amazon.com`



(6.4.1) F_{DM} value over time



(6.4.2) F_{RT} value over time



(6.4.3) F_{CU} value over time

Figure 6.4. Objective values of F_{DM}, F_{RT}, and F_{CU} over time, where we highlighted the time when the first incumbent predicted to violate a performance requirement was found

support stress testing of task deadlines, and is therefore a natural comparison baseline. To successfully enable our empirical study, we slightly modified the original GA approach. Specifically, (1) we added the support for multi-core platforms, as the original work was meant for analyzing only software systems running on single-core architectures, and (2) we replaced the original fitness function with the F_{DM} defined in Section 6.1.4, in order to account for the deadline misses for all tasks, rather than for a single target task.

The comparison is performed on five subject systems from safety-critical domains reported in the literature, briefly described in Section 6.2.2.1. The goal of our study is to answer the research questions presented in Section 6.2.2.2 based on the metrics and attributes detailed in Section 6.2.2.3. The design of our experiment is described in Section 6.2.2.4, and its results are discussed in Section 6.2.2.5. Finally, Section 6.2.2.6 covers some potential threats that could affect the general validity of our conclusions.

6.2.2.1 Subject Systems

To investigate the general performance of GA and CP in a variety of conditions, we selected five subject systems from safety-critical domains with varying size and complexity. Specifically, our comparison is based on one system from the aerospace domain, two systems from the automotive domain, and two from the avionics domain. The systems presented in the following subject systems share the most common characteristics of safety-critical RTES: they are integrated with the physical domain by interacting with external devices such as sensors and actuators, they have a concurrent design, and they are subject to timing requirements ranging in the order of milliseconds.

- **Ignition Control System (ICS).** Bosch GmbH[2] developed an ignition control system of an automotive engine [Peraldi-Frati and Sorel, 2008]. The system features sensors and actuators to sample physical phenomena such as knock, temperature variation and engine warm-up, and to perform corrections over them for a successful ignition of a spark plug in the engine.
- **Cruise Control System (CCS).** Continental AG[3] developed a Cruise Control System deployed on AUTOSAR-compliant architectures [Anssi et al., 2011]. The system features a switch sensor that acquires driver inputs (e.g., set/cancel cruise, increase/decrease speed), and a control system that processes the inputs and maintains the specified vehicle speed.
- **Unmanned Air Vehicle (UAV).** The ENSMA[4], together with the University of Poitiers in France, worked on a joint project for a mini Unmanned Air Vehicle named AMADO [Traore et al., 2006]. The system embeds a camera to be able to follow dynamically defined way-points, and is connected to a ground station via a wireless modem that allows it to receive instruction data during a mission.
- **Generic Avionics Platform (GAP).** The Carnegie-Mellon University in Pennsylvania, together with the US Naval Weapons Center[5] and the IBM Federal Sector Division[6], designed a specification for a hypothetical avionics software mission control computer of a military aircraft [Locke et al., 1990]. Though the system can be configured to fit several possible missions, the specification is targeted for the specific case of an air-to-surface attack.
- **Herschel-Planck Satellite System (HPSS).** The European Space Agency[7] carried out the Herschel-Planck Mission consisting of the two satellites Herschel and Planck [Mikučionis et al., 2010]. The satellites have different scientific purposes: Herschel carries a large infrared telescope, while Planck is a space observatory for studying the Cosmic Microwave Background. The satellites share the same computational architecture composed of a real-time operating system, a basic software layer, and application software.

Table 6.1 summarizes relevant data from the systems specifications, reported in ascending order of size and complexity. Specifically, we take into account the number of software tasks, inter-dependencies, triggering relations, and platform cores. This data has been extracted from the sources cited above, which

[2] http://www.bosch.com
[3] http://www.conti-online.com
[4] http://www.ensma.fr
[5] http://www.navair.navy.mil/nawcwd
[6] http://www.ibm.com/federal
[7] http://www.esa.int

include full descriptions of the systems. The complete version of the data extracted is available on-line as a technical report[8].

System	Software System				Platform	Logsize
	Tasks		Relationships		Cores	
	Periodic	Aperiodic	Dependencies	Triggering		
ICS	3	3	3	0	3	446.7
CCS	8	3	3	6	2	551.6
UAV	12	4	4	0	3	671.5
GAP	15	8	6	5	2	709.4
HPSS	23	9	5	0	1	836.6

Table 6.1. Subject systems data

To investigate the impact that the target system complexity has over the practical usefulness of the search strategies, we also quantified the system size. Specifically, we define the size of each system as the size of its associated search space, that is the product of the domain size of the search variables (Section 6.1.2). Indeed, the search space contains by definition all the feasible assignments of values to variables in the problem. The last column of the table reports the base 2 logarithm of the size of the search space. For example, in ICS there are ca. $2^{446.7}$ possible ways in which tasks could arrive and be scheduled for execution.

6.2.2.2 Research Questions

The goal of our empirical study is to answer the following research questions involving GA and CP for the purpose of supporting stress testing of task deadlines.

RQ1 — Efficiency. *Does one search strategy find the best solutions significantly faster than the other?*

RQ2 — Effectiveness. *Does one search strategy find significantly better solutions (i.e., solutions with worse deadline misses) than the other?*

RQ3 — Scalability. *To what extent does the size of a system affect the efficiency of the two search strategies?*

RQ1 and RQ2 are investigated through a set of metrics and attributes detailed in Section 6.2.2.3. The goal of such metrics and attributes is to provide quantitative evidence to answer the research questions. On the other hand, RQ3 is discussed only qualitatively in Section 6.2.2.5. This is because we base our analysis of efficiency on a set of five subject system, and therefore no quantitative study, for example based on regression analysis, can be carried out to identify precise trends.

[8] `http://home.simula.no/~stefanod/data.pdf`

6.2.2.3 Comparison Metrics and Attributes

Though the search for optimal solutions is driven by the function F_{DM} defined in Section 6.1.4, we broke down the function into several factors that are of practical interest while investigating worst case scenarios for deadline misses. This is because, to properly answer the research questions, one must look into several complementary aspects of F_{DM}. For this reason, we defined the efficiency and effectiveness properties related to RQ1 and RQ2 as *attributes*, and we defined a set of *metrics* to enable their measurement. Therefore, we compare the performance of GA and CP by collecting data pertaining to the metrics and attributes defined below. To enable a formal definition of metrics and attributes, we introduce the following notation:

Search Strategy. *Let* Γ *denote the search strategies:* $\Gamma \in \{GA, CP\}$.

Target System. *Let* Σ *denote the systems described in Section 6.2.2.1:* $\Sigma \in \{ICS, CCS, UAV, GAP, HPSS\}$.

Set of Solutions. *Let* $X(\Gamma, \Sigma)$ *denote the set of solutions found by the search strategy* Γ *during an experiment on the target system* Σ.

6.2.2.3.1 Comparison Metrics The following metrics are defined for a given solution $x \in X$ found by the search strategy Γ during an experiment on the target system Σ. In the definitions, we omit the dependency from Γ and Σ for the sake of readability. Recall that a solution x is defined as a sequence of arrival times $x_{j,k}$ for each aperiodic task, i.e., $x = \left[[x_{j,k} \mid k \in K_j] \mid j \in J_a\right]$. We use an alternative notation for the variables when in need to make their context explicit. In such notation, the indexes j, k and p are reported as subscripts, and the parentheses contain the specific context that the variable refer to. Examples of contexts for variables are the system Σ under analysis, the search strategy Γ used, or the solution x the properties belong to. For instance, we write $dm_{j,k}(x)$ to mean the value of $dm(j,k)$ in the solution x.

Computation time. *We define* $t(x)$ *as the time required to find solution x, from when the search starts.*

The sum of time quanta in all deadline misses is strongly related to the value of the fitness/objective function that guides the search. In practice, the sum of time quanta in deadline misses provides some insight into the magnitude of the identified deadline misses. Since our approach is based on task execution time estimates, the larger the sum of deadline misses, the more likely tasks are to miss their deadlines at runtime.

Sum of time quanta in deadline misses. *We define* $s(x)$ *as the sum of time quanta in all deadline misses of solution x. Recall from Section 6.1.1 that, for a given solution x, we define* $dm(j,k) \overset{def}{=} en(j,k) - dl(j,k)$.

$$s(x) \overset{def}{=} \sum_{j \in J,\, k \in K_j(x)} max\Big(0,\, dm_{j,k}(x)\Big)$$

The number of tasks that miss a deadline is relevant for generating stress test cases for task deadlines as, in practice, every task that misses a deadline has to be looked into and possibly re-designed. Hence, not realizing that a task can miss its deadline may lead to overlooking an important flaw.

Number of tasks that miss a deadline. *We define $n(x)$ as the number of tasks that miss at least a deadline in solution x.*

$$n(x) \overset{def}{=} \left| \left\{ j \in J \mid \exists k \in K_j(x) \cdot dm_{j,k}(x) \geq 0 \right\} \right|$$

The number of task executions that miss a deadline is also of interest as, in soft real-time systems, one could tolerate less critical tasks missing some deadlines, provided that the frequency of deadline misses is acceptable. Therefore, overestimating this number might lead us to inspect a task when unnecessary, while underestimating it could lead to overlooking tasks that frequently miss their deadlines.

Number of task executions that miss a deadline. *We define $m(x)$ as the number of task executions that miss a deadline in solution x.*

$$m(x) \overset{def}{=} \left| \left\{ k \in K_j(x) \mid j \in J \wedge dm_{j,k}(x) \geq 0 \right\} \right|$$

Note that, by definition, $\forall x \in X \cdot m(x) \geq n(x)$.

We note how the metrics s, n, and m also capture the general *quality* of a solution. Intuitively, higher values for s, n and m, all correspond in a different way to higher quality solutions. Specifically, solutions with many large deadline misses or many tasks or task executions that miss a deadline characterize worst case scenarios. Therefore, a *best* solution can be identified only with respect to a specific metric. For each search strategy Γ running during an experiment on the target system Σ, we define the following quantities:

Largest sum of time quanta in deadline misses. *We define s^* as the largest sum of time quanta in deadline misses in X.*

$$s^* \overset{def}{=} \max_{x \in X} s(x)$$

Largest number of tasks missing their deadline. *We define n^* as the largest number of tasks missing their deadline in X.*

$$n^* \overset{def}{=} \max_{x \in X} n(x)$$

Largest number of task executions missing their deadline. *We define m^* as the largest number of task executions missing their deadline in X.*

$$m^* \overset{def}{=} \max_{x \in X} m(x)$$

Set of best solutions with respect to the sum of time quanta in deadline misses. *We define X_s^* as the set of best solutions with respect to the sum of time quanta in deadline misses.*

$$X_s^* \overset{def}{=} \{x \in X \mid s(x) = s^*\}$$

Set of best solutions with respect to the number of tasks missing their deadline. *We define X_n^* as the set of best solutions with respect to the number of tasks missing their deadline.*

$$X_n^* \overset{def}{=} \{x \in X \mid n(x) = n^*\}$$

Set of best solutions with respect to the number of task executions missing their deadline. *We define X_m^* as the set of best solutions with respect to the number of task executions missing their deadline.*

$$X_m^* \overset{def}{=} \{x \in X \mid m(x) = m^*\}$$

6.2.2.3.2 Comparison Attributes

We introduce two comparison attributes to capture two aspects of practical interest while testing. Indeed, a test suite has two desirable properties:

1. It is computed in the shortest possible time, and,
2. It contains test cases that are as likely as possible to push tasks to miss their deadlines at runtime

Efficiency captures the first property, measuring how quickly a search strategy converges to the optimal solutions it finds. *Effectiveness* captures the second property, measuring how likely are the solutions found to characterize stress cases that reveal deadline misses at runtime. The comparison attributes are also defined for each search strategy Γ running during an experiment on the target system Σ.

The more efficient a strategy, the faster it computes its best solutions. Therefore, the efficiency attribute relates to RQ1 and RQ3.

Efficiency. *We define the efficiency η with respect to a given metric as the minimum time required to compute one of the best solutions with respect to that metric. Specifically, we define the efficiency with respect to s, m, and n.*

$$\eta_s \overset{def}{=} \min_{x \in X_s^*} t(x) \qquad \eta_n \overset{def}{=} \min_{x \in X_n^*} t(x) \qquad \eta_m \overset{def}{=} \min_{x \in X_m^*} t(x)$$

The more effective a strategy, the better the solutions it computes. Therefore, the effectiveness attribute relates to RQ2.

Effectiveness. *We define the effectiveness κ with respect to a given metric as the value of that metric for the best solutions found. Specifically, we define effectiveness with respect to s, m, and n.*

$$\kappa_s \overset{def}{=} s^* \qquad \kappa_n \overset{def}{=} n^* \qquad \kappa_m \overset{def}{=} m^*$$

6.2.2.4 Experiments Setup

To answer RQ1 and RQ2, we performed a series of experiments over the systems described in Section 6.2.2.1. The experimental design is illustrated in Figure 6.5. Each experiment consisted of running both search strategies on a target system for a number of times, each run having the same duration. To provide an initial assessment of the practical usefulness of GA and CP, we chose to run each strategy on a desktop computer for one hour. To do so, we set up GA to continuously generate new solutions for one hour, while we set up CP to terminate the search after one hour. Running both strategy for the same amount of time allows us to meaningfully compare their effectiveness. Furthermore, during the design of the experiment, we had to consider the inherent randomized behavior of GA in contrast to the fully deterministic behavior of CP. Indeed, GA finds solutions starting from a randomly chosen initial population of individuals by applying crossover and mutation operators with a given probability, while CP finds solutions by solving a COP. For this reason, while we ran CP only once for one hour for each system, we ran GA 50 times for one hour on each system. In this way, we could compute distributions of the best solutions recorded over 50 runs over the efficiency and effectiveness ranges. For each experiment, we recorded only the 100 solutions with the highest fitness/objective value found by GA and CP. This is because each solution characterizes a stress test case, and 100 has proven to be a satisfactory number of observations to meaningfully compare two distributions [Arcuri and Briand, 2011]. Since RQ1 and RQ2 are related to attributes η and κ respectively, for each solution we computed the values of the metrics t, s, n, and m used to define such attributes. Both GA and CP have been run one at a time on the same machine, i.e., a desktop computer with a 3.3 Ghz dual-core Intel Core i3 processor, and 8GB RAM.

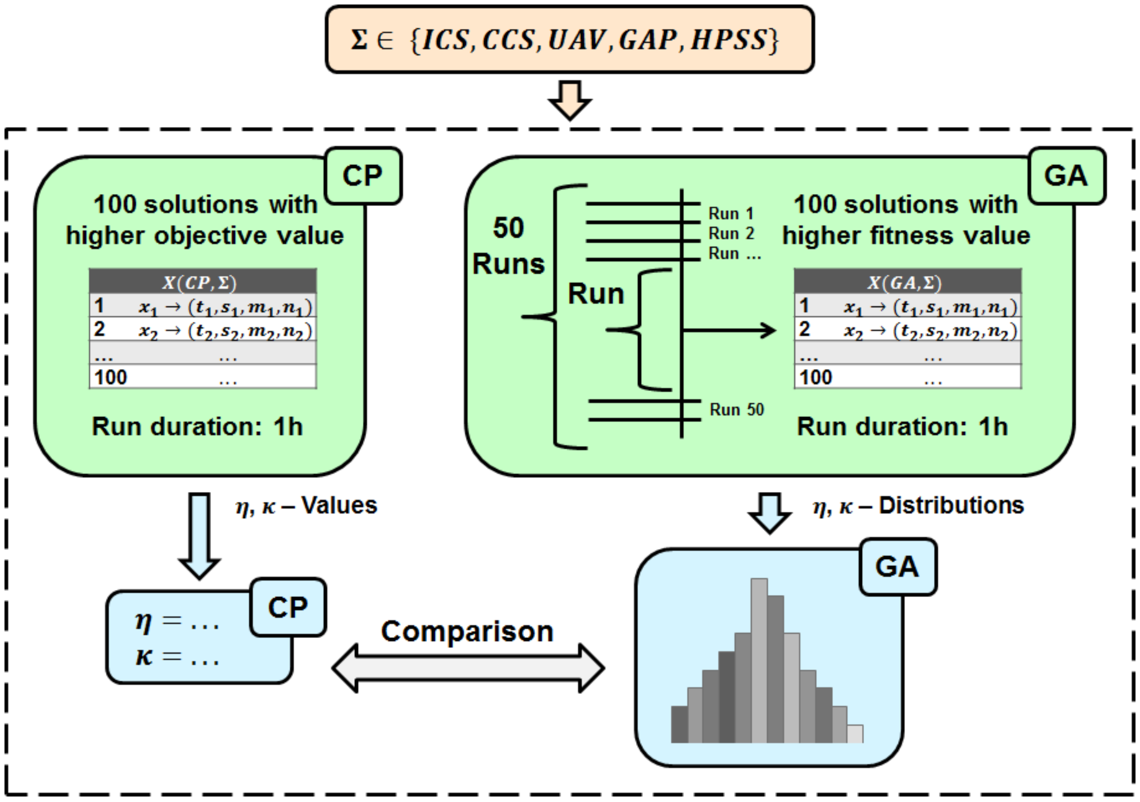

$\Sigma \in \{ICS, CCS, UAV, GAP, HPSS\}$
CP
100 solutions with higher objective value
$X(CP,\Sigma)$
1 $x_1 \rightarrow (t_1, s_1, m_1, n_1)$
2 $x_2 \rightarrow (t_2, s_2, m_2, n_2)$
100
Run duration: 1h
GA
50 Runs
Run
Run 1
Run 2
Run ...
Run 50
100 solutions with higher fitness value
$X(GA,\Sigma)$
1 $x_1 \rightarrow (t_1, s_1, m_1, n_1)$
2 $x_2 \rightarrow (t_2, s_2, m_2, n_2)$
100
Run duration: 1h
η, κ – Values
η, κ – Distributions
CP
$\eta = \dots$
$\kappa = \dots$
Comparison
GA

Figure 6.5. Experimental design: we run CP a single time recording the 100 solutions with highest objective value, and calculating a single value for each metric. Then, we run GA 50 times recording the 100 solutions with highest fitness value, and calculating distributions for the metrics.

6.2.2.5 Results and Discussion

Table 6.2 reports the efficiency η with respect to s, n and m for GA and CP and for each system. The computation times for the best solutions are reported in the format *mm:ss*. In place of reporting the full distributions of GA, we report instead a set of statistics that meaningfully represent the efficiency of GA across runs, specifically:

- The mean computation time $\bar{x}$ of the best solution
- The three quartiles Q_1, Q_2, and Q_3 of the computation time of the best solution
- The probability P that GA achieves a greater or equal efficiency than CP. P is calculated as the percentage of runs in which GA had a greater or equal efficiency than CP, i.e., the percentage of runs in which GA found its best result before or at the same time as CP found its own.

Being deterministic, the column of CP reports instead the single computation times of the best solutions.

System	η_s			η_n			η_m		
	GA		CP	GA		CP	GA		CP
ICS	$\bar{x}$	15:23	40:23	$\bar{x}$	11:05	40:23	$\bar{x}$	11:05	40:23
	Q_1	09:33		Q_1	04:33		Q_1	04:33	
	Q_2	14:07		Q_2	07:49		Q_2	07:49	
	Q_3	18:05		Q_3	13:32		Q_3	13:32	
	P	0.98		P	1		P	1	
CCS	$\bar{x}$	24:42	18:04	$\bar{x}$	07:20	18:04	$\bar{x}$	07:20	18:04
	Q_1	15:09		Q_1	05:19		Q_1	05:19	
	Q_2	22:33		Q_2	06:48		Q_2	06:48	
	Q_3	30:52		Q_3	08:16		Q_3	08:16	
	P	0.36		P	1		P	1	
UAV	$\bar{x}$	42:01	01:05	$\bar{x}$	39:50	00:37	$\bar{x}$	39:50	00:37
	Q_1	33:39		Q_1	32:49		Q_1	32:49	
	Q_2	38:34		Q_2	37:11		Q_2	37:11	
	Q_3	53:29		Q_3	48:19		Q_3	48:19	
	P	0		P	0		P	0	
GAP	$\bar{x}$	40:26	22:38	$\bar{x}$	21:07	01:38	$\bar{x}$	30:03	01:38
	Q_1	33:00		Q_1	06:30		Q_1	10:59	
	Q_2	40:32		Q_2	12:47		Q_2	34:50	
	Q_3	50:22		Q_3	34:20		Q_3	42:48	
	P	0.1		P	0		P	0	
HPSS	$\bar{x}$	20:19	05:56	$\bar{x}$	20:19	00:54	$\bar{x}$	20:19	00:54
	Q_1	14:31		Q_1	14:31		Q_1	14:31	
	Q_2	17:51		Q_2	17:51		Q_2	17:51	
	Q_3	22:30		Q_3	22:30		Q_3	22:30	
	P	0		P	0		P	0	

Table 6.2. Experimental results for efficiency η

6.2.2.5.1 RQ1 — Efficiency We observe how, on the two smallest subject systems, GA has a consistently better efficiency than CP. Specifically, in ICS, GA was able to find on average the best solutions x_s^*,

x_n^*, and x_m^* three or four times faster than CP. We can identify this trend also in CCS, where we recorded the same efficiency gap with the exception of η_s, where the efficiency of CP is achieved by GA by the second quartile. However, for the three largest systems, CP is significantly faster than GA at finding the best results with respect to s, n, and m. The efficiency of CP is indeed far above the one observed before the third quartile of GA. With the exception of η_s in GAP, no GA run was faster at finding its best result than CP.

Table 6.3 reports the effectiveness κ with respect to s, n, and m for GA and CP and for each system. As for Table 6.2, the columns of GA report statistics about the distribution of effectiveness:

- The mean value $\bar{x}$ of the best solution
- The three quartiles Q_1, Q_2, and Q_3 of the value of the best solution
- The probability P that GA achieves a greater or equal effectiveness than CP. P is calculated as the percentage of runs in which GA had a greater or equal effectiveness than CP, i.e., the percentage of runs in which the best result found by GA was better than or equal to the best result found by CP.

The column of CP reports instead the single value of the best solutions.

6.2.2.5.2 RQ2 — Effectiveness We observe how, on the two smallest subject systems, the effectiveness of GA is on average similar to the effectiveness of CP. In ICS, GA reaches by the third quartile the same result as CP for κ_s, κ_n, and κ_m. In CSS instead, GA reaches by the second quartile the same result as CP for κ_s, and does so by the first quartile for both κ_n and κ_m. However in both cases, though the solutions found by CP are better on average, the efficiency of GA is superior to the efficiency of CP. This means that there is a high probability that in few runs GA finds the same best solutions with respect to s, n, and m as CP. For the three largest systems instead, with the exception of UAV for κ_n and κ_m, CP finds significantly better values than GA for s, n, and m. Specifically, in UAV GA finds on average one deadline miss of one time quantum, while CP finds one deadline miss of three time quanta. The difference in κ_s between GA and CP increases in GAP and HPSS. In GAP, GA has an average value of 19 for κ_s, while CP achieves 34 half of the time. In HPSS, GA hardly finds any deadline miss, while CP finds one of five time quanta after a few minutes. These differences in the value of κ_s are of practical significance because, as discussed above, a larger sum of deadline misses indicates scenarios where tasks are more likely to miss their deadlines at runtime. Furthermore, for all subject systems, no GA run found a better solution than CP.

6.2.2.5.3 RQ3 — Scalability In light of these results, we conclude that, for the smaller subject systems, GA has proven to be more efficient than CP, and nearly as effective. On the other hand, for the larger systems, CP has proven to be significantly more efficient and more effective than GA. The outcome of this experiments seems to suggest that, within the range covered by our systems and the proposed experimental design, the larger the size of the system, the better CP when compared to GA.

6.2.2.5.4 Summary and Discussion We conjecture that the reason for this trend stems from the interaction between the size of the search space of the subject systems, and the heuristics used in our CP

System	κ_s			κ_n			κ_m		
	GA		CP	GA		CP	GA		CP
ICS	$\bar{x}$	13.22	19	$\bar{x}$	1.3	2	$\bar{x}$	1.3	2
	Q_1	14		Q_1	1		Q_1	1	
	Q_2	14		Q_2	1		Q_2	1	
	Q_3	19		Q_3	2		Q_3	2	
	P	0.26		P	0.32		P	0.32	
CCS	$\bar{x}$	12.14	13	$\bar{x}$	2	2	$\bar{x}$	2	2
	Q_1	11		Q_1	2		Q_1	2	
	Q_2	13		Q_2	2		Q_2	2	
	Q_3	13		Q_3	2		Q_3	2	
	P	0.52		P	1		P	1	
UAV	$\bar{x}$	0.94	3	$\bar{x}$	0.74	1	$\bar{x}$	0.74	1
	Q_1	0		Q_1	0		Q_1	0	
	Q_2	1		Q_2	1		Q_2	1	
	Q_3	1		Q_3	1		Q_3	1	
	P	0.02		P	0.74		P	0.74	
GAP	$\bar{x}$	19.18	34	$\bar{x}$	2.4	3	$\bar{x}$	3.06	5
	Q_1	16		Q_1	2		Q_1	3	
	Q_2	19		Q_2	2		Q_2	3	
	Q_3	21		Q_3	3		Q_3	4	
	P	0		P	0.4		P	0.02	
HPSS	$\bar{x}$	0.04	5	$\bar{x}$	0.04	1	$\bar{x}$	0.04	1
	Q_1	0		Q_1	0		Q_1	0	
	Q_2	0		Q_2	0		Q_2	0	
	Q_3	0		Q_3	0		Q_3	0	
	P	0		P	0.04		P	0.04	

Table 6.3. Experimental results for effectiveness κ

solution. The size of the search space is largely determined by the number of aperiodic task executions within the observation time interval. The systems where GA is more efficient than CP, i.e., ICS and CCS, have a smaller search space, and hence, GA is able to quickly converge towards the best solutions regardless of its initial population. Therefore, in these systems GA performs reasonably well compared to CP. On the other hand, in systems with large search spaces, i.e., UAV, GAP, HPSS, GA needs more time to converge towards its best solution. Thanks to its heuristic, CP is able to find solutions with a rather high objective value in a few minutes.

Note that the efficiency and effectiveness results of the search strategies are obtained by running them for one hour. Due to this time limit, in the larger systems, CP may fail at further improving the solutions that it finds at the very beginning of its search. Indeed, if the GA and CP had been run for longer time on the larger systems, we might have obtained better solutions that take much longer to compute. Analyzing the experimental results, we found out that running GA and CP for one hour can provide only a rough assessment on the efficiency and effectiveness of both strategies, and on the way the system size affects efficiency and effectiveness. For this reason, we further investigated the performance of GA and CP in another series of experiments, where we run each strategy for 10 hours. This second series of experiments, discussed in Section 7.2, showed a clear trend, where GA is more efficient, while CP is more effective. This second experiment motivated us in devising a combined strategy (Chapter 7) that aims at retaining the advantages of GA and CP.

6.2.2.6 Threats to Validity

We identified three main threats that could affect the general validity of our conclusions: First, the analysis of efficiency, effectiveness and scalability is based on a set of five subject systems. Although comparing GA and CP in a larger number of systems would have mitigated this threat, the systems have been selected from different RTES domains and feature varying size and complexity.

Second, the size of the selected systems varies from 6 to 32 tasks, 3 to 9 of which aperiodic. There could be much larger systems featuring hundreds of tasks, and for those the efficiency and effectiveness of CP need to be investigated. This means that the conclusions drawn are valid only for systems in the same size range of the subject systems used in the comparison.

Third, the experiment set-up relies on the choice of running both search strategies for one hour, and on specific parameters used for GA, such as the initial population size, the crossover and mutation probabilities, and the population replacement rate. Different values for these parameters could have led to higher efficiency and effectiveness. However, we used the same values as in the work of Briand et al. [Briand et al., 2006], that have been derived from the GA literature and specifically tuned for deadline misses analysis. However, by looking at the quartiles of the efficiency distributions, GA did not find always find its best results significantly earlier than one hour. This means that, in most cases, GA did not reach a plateau before one hour, and there are chances for it to find a better solution if given more time. To mitigate this threat, we should investigate the efficiency and effectiveness in an experiment where GA and CP are run for longer time. As discussed at the end of Section 6.2.2.5, this longer experiment is discussed in Section 7.2.

Chapter 7

Combining Genetic Algorithms and Constraint Programming to Automate the Generation of Stress Test Cases

In Chapter 6 we discussed a strategy based on Constraint Programming (CP) to automate the generation of stress test cases to break task deadlines. The strategy is based on the definition of a Constraint Optimization Problem (COP) for the purpose of generating sequences of arrival times likely to lead to deadline misses. The COP models the properties of the system as integer constants and variables, and models the scheduler of the system as a set of constraints among such variables. The generation of stress test cases is driven by an objective function that expresses the likelihood of the arrival times to violate a given performance requirement. In particular, we defined the objective function F_{DM} expressing the extent to which a particular set of arrival times is predicted to break task deadlines. Also recall from Section 2.4.2.2 that Genetic Algorithms (GA) have been used in the past to support stress testing of task deadlines. Among others, Briand et al. proposed a GA-based search strategy [Briand et al., 2006] to generate sequences of arrival times likely to lead to deadline misses. In that work, arrival times of aperiodic tasks are modeled as chromosomes. The initial population of these chromosomes is initialized with random values, and their fitness is evaluated by computing the tasks schedule that is produced from the arrival times encoded in the chromosomes. Indeed, such a schedule contains information about the end times of tasks, which belong to the fitness function in a fashion similar to that of F_{DM}. At each iteration of GA, a pair of chromosomes is crossed over and then mutated using specific operators that ensure compliance with the inter-arrival times of aperiodic tasks.

Preliminary experimental results have shown in some cases an opposing trend: while GA was more *efficient*, i.e., faster in generating test cases, CP was more *effective*, i.e., it generated test cases that were more likely to identify deadline misses. Furthermore, GA was able to find a larger and more diverse set of test cases than CP, exercising the system in a more *diverse* way with respect to task executions. Specifically, the test cases generated by GA had a higher variety in terms of 1. time span and 2. preemptions between task executions, and 3. number of aperiodic task executions. These three criteria are described in Section 7.2.2 and define the concept of test case *diversity*. On the other hand, CP generated a smaller number of test cases, most of which were redundant with respect to the three criteria, i.e., executed the system tasks during similar time intervals, with the same preemptions and number of executions.

Therefore, we looked into a way to achieve both the efficiency of GA and the effectiveness of CP. The key idea behind this new stress testing strategy is to improve the solutions computed by GA by performing a complete search with CP in their neighborhood, hence defining a two-stage GA+CP strategy. In this way, we expected the combined approach to take advantage of the efficiency of GA, because solutions are initially computed with GA and the subsequent CP search is likely to terminate in a short time since it focuses on the neighborhood of a solution, rather than in the whole search space. Similarly, we expected GA+CP to take advantage of the solutions diversity of GA, because these solutions define in turn subspaces where CP searches for better solutions. Finally, we also expected GA+CP to take advantage of the effectiveness of CP since, after GA computes a solution, CP either finds the best solution within the neighborhood, or proves upon termination that no better solution exists in such neighborhood.

7.1 A hybrid GA+CP strategy to Automate the Generation of Stress Test Cases

We refine our strategy for determining worst-case schedules of tasks with an approach motivated by our experimental results on the comparison between the CP-based and GA-based strategies (Section 6.2.2). Specifically, we solve the search for arrival times of aperiodic tasks with a two-step strategy. The key idea behind the strategy is to first generate a set of solutions with GA, and then perform a series of local searches with CP in the neighborhood of those solutions. Figure 7.1 illustrates how GA+CP searches for solutions through an abstract example.

1. **GA Step.** The initial population of GA consists of the three solutions x_1, y_1, and z_1. In the first generation, GA finds the solutions x_2, y_2, and z_2 that are generated from x_1, y_1 and z_1 respectively. After the five generations, GA converges on the solutions x_6, y_6 and z_6.
2. **CP Step.** CP then searches for better solutions in the neighborhoods of x_6, y_6 and z_6. This step is performed by launching three separate instances of CP, each having x_6, y_6 and z_6 as a starting point. The first two complete searches find the solutions x^* and y^*. The last proves upon termination that z_6 is the best solution in its neighborhood, hence $z_6 = z^*$. Therefore, x^*, y^*, and z^* are the final solutions found by GA+CP, and are used to characterize stress test cases.

We begin the formal description of our approach by introducing the following notation.

Recall that a solution is a sequence of arrival times which the search identifies as likely to break task deadlines, and hence characterizes a stress test case.

Solution computed by GA. *Let* $x = \Big[[x_{j,k} \mid k \in K_j] \mid j \in J_a\Big]$ *denote a solution computed by GA.*

Note that, by definition, x is an assignment of arrival times for aperiodic tasks, where $x_{j,k}$ is the value for the k^{th} arrival time of task j: $\forall j \in J_a,\ k \in K_j \cdot at_{j,k}(x) = x_{j,k}$.

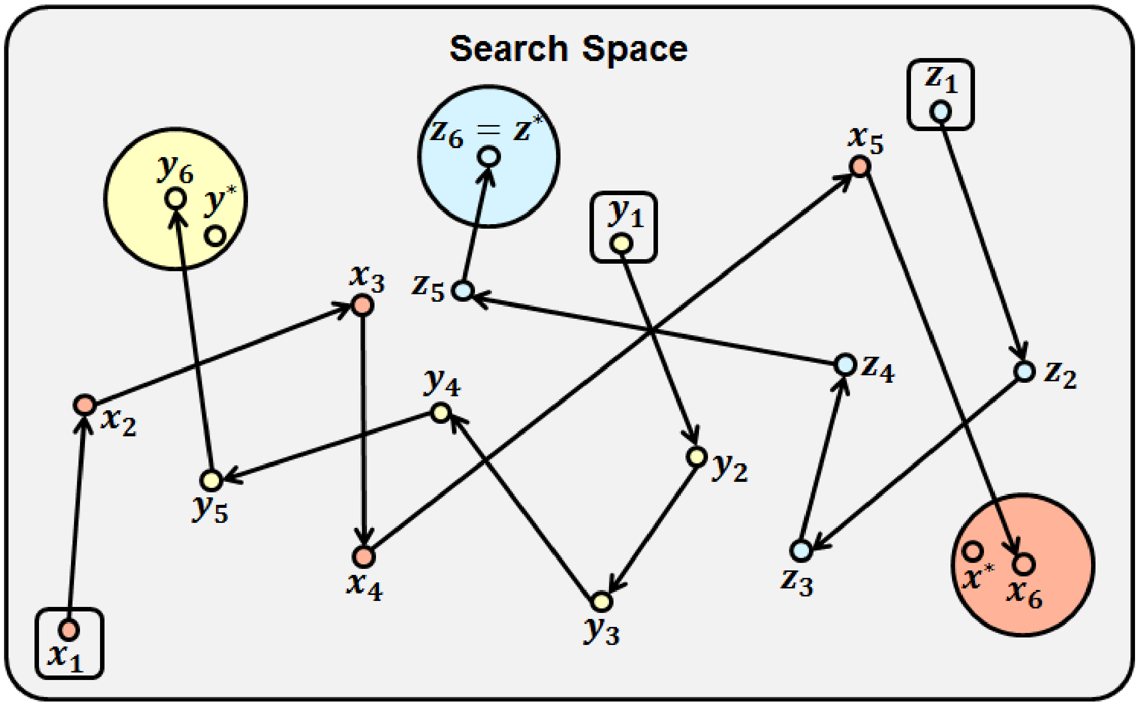


Figure 7.1. Overview of GA+CP: the solutions x_1, y_1 and z_1 in the initial population of GA evolve into x_6, y_6, and z_6, then CP searches in their neighborhood for the optimal solutions x^*, y^* and z^*.

Consider two tasks j_1 and j_2 such that the arrival time of an execution of j_1 can have a *direct* impact over an execution of j_2. In practice, this can happen in two cases. The first case occurs if j_1 has higher priority than j_2. In this case, j_2 can be preempted at any time by j_1 if there are not enough cores available. The second case occurs when j_1 and j_2 share the same computational resource. In this case, if j_1 arrives before j_2 has acquired the lock on the resource, the latter will have to wait until such lock is released. Therefore, we define the *impacting relation* between two tasks in the following way:

Impacting Relation between two tasks. *We define im as a binary relation defined over $J \times J$ holding if the arrival time of an execution of j_1 can have a* direct *impact over an execution of j_2:*

$$im(j_1, j_2) \overset{def}{=} pr(j_1) \geq pr(j_2) \vee de(j_1, j_2)$$

Note that *im* is defined reflexive, because trivially the arrival time of a task has an impact over the execution of the task itself. However, j_1 having higher priority or depending on j_2 is not the only case in which j_1 can have an in impact over an execution of j_2. For instance, consider the case where j_1 has higher priority than another task j_3, and j_3 depends on j_2. In this case, j_1 could preempt j_3 after j_3 has acquired the lock on the resource shared with j_2, and then j_2 would have to wait for both the completion of j_1 and j_3 before being able to execute. In this case, j_1 can also have an impact over an execution of j_2, albeit this impact is *indirect* since it involves j_3. For this reason, we denote the transitive closure of *im* as im^+, in order to cover all the cases where j_1 can have a direct or indirect impact over the execution of j_2.

Impacting Set of a Task. *Let $I : J \rightarrow \mathcal{P}(J)$ be the function that represents the set of tasks that can have an impact over the execution of a target task: $I_j \overset{def}{=} \{j' \in J \mid im^+(j', j)\}$. We define I_j as the impacting set of j.*

Set of tasks that miss a deadline or are the closest to miss it among all tasks. *We define $J^*(x)$ as the set of tasks that miss at least a deadline in one execution, or are closer than others to doing so in the schedule generated by the arrival times in x.*

$$J^*(x) \overset{def}{=} \Big\{ j \in J \,\Big|\, \exists k^* \in K_{j^*}(x) \cdot \big(dm_{j^*,k^*}(x) \geq 0 \vee \\ \forall j \in J,\, k \in K_j \cdot dm_{j^*,k^*}(x) \geq dm_{j,k}(x)\big)\Big\}$$

Union set of impacting sets of tasks missing or closest to miss their deadlines. *We define $I^*(x)$ as the union of the impacting sets of tasks in $J^*(x)$.*

$$I^*(x) \overset{def}{=} \bigcup_{j^* \in J^*(x)} I_{j^*}(x)$$

By definition, $I^*(x)$ contains all the tasks that can have an impact over a task that misses a deadline or is closest to a deadline miss.

Neighborhood of an arrival time and neighborhood size. *We define $\varepsilon_D(x_{j,k})$ as the neighborhood of $x_{j,k}$ of size D, i.e., as the interval centered in the arrival time $x_{j,k}$ whose radius is D.*

$$\varepsilon_D(x_{j,k}) \overset{def}{=} [x_{j,k} - D,\; x_{j,k} + D]$$

ε defines the part of the search space around $x_{j,k}$ where to find arrival times that are likely to break task deadlines. Note that D is a parameter of the search.

Constraint Model Implementing a Complete Search Strategy. *Let $\mathcal{M}$ denote the constraint model defined in Section 6.1 that considers the function F_{DM} (Section 6.1.4) for the purpose of identifying task arrival times that are likely to break deadlines.*

$\mathcal{M}$ models the static and dynamic properties of the software system as constants and variables respectively, and the scheduler of the operating system as a set of constraints among such variables. Note that $\mathcal{M}$ is solved a using a complete search strategy over the space of arrival times. This means that $\mathcal{M}$ searches for arrival times of all aperiodic tasks within the whole interval T.

Our combined GA+CP strategy consists of the following two steps:

1. **GA Step.** Run GA for a given amount of time to obtain a set X of solutions. For this purpose, we use the implementation of GA introduced by Briand et al., with the same initial population size, replacement strategy, and probability values used for crossover and mutation [Briand et al., 2006].

2. **CP Step.** For each solution $x \in X$, solve a constraint model $\mathcal{M}'(x)$ that searches for arrival times only within a fixed-size neighborhood of x.

$\mathcal{M}'(x)$ is derived from $\mathcal{M}$ by:

- *Fixing the arrival time of tasks not in I^*.* This is done by adding to $\mathcal{M}$ the following constraint:

  $$\forall j \in J \setminus I^*(x),\ k \in K_j(x) \cdot at(j,k) = x_{j,k}$$

  In practice, this means that the arrival time of all task executions that do not have any impact on tasks being close to missing a deadline will be fixed in $\mathcal{M}'$.
- *Bounding the arrival times of tasks in I^*.* This is done by adding to $\mathcal{M}$ the following constraint:

  $$\forall j \in I^*(x),\ k \in K_j(x) \cdot x_{j,k} - D \leq at(j,k) \leq x_{j,k} + D$$

  In practice, this means that the arrival time of the task executions that can have an impact on tasks identified by GA as close to missing a deadline will be declared in M' as a variable with domain $\varepsilon(x_{j,k})$.

Note that, by definition, $\mathcal{M}'$ implements a local search strategy over the search space of arrival times. This means that $\mathcal{M}'$ searches only for arrival times of aperiodic tasks that can have an impact on tasks GA identifies as close to missing a deadline, and bounds the search within a neighborhood of size D from the solution computed by GA. Specifically, for given j and k, the inequality constraints on the variable *at* define in the solutions space a hypercube of side $2D$ centered in $x_{j,k}$.

The search in GA+CP can be configured through two sets of parameters, one related to GA and the other to CP. GA relies on parameters specific to evolutionary algorithms, such as the initial population size, the crossover and mutation probabilities, and the population replacement rate. For those, we used values that have been derived from the GA literature and specifically tuned for deadline miss analysis [Briand et al., 2006]. On the other hand, CP is a deterministic search strategy, and therefore does not require us to set such parameters. However, our combined search strategy depends on the neighborhood size D that CP searches for arrival times of aperiodic tasks. Our preliminary experimentation showed that a value of D around 1% of T yields a good compromise between efficiency and effectiveness. Specifically, lower values for D define a smaller neighborhood where GA+CP is less likely to improve the solutions found by GA, while higher values for D define a larger neighborhood where GA+CP is likely to spend a significant amount of time without finding better solutions.

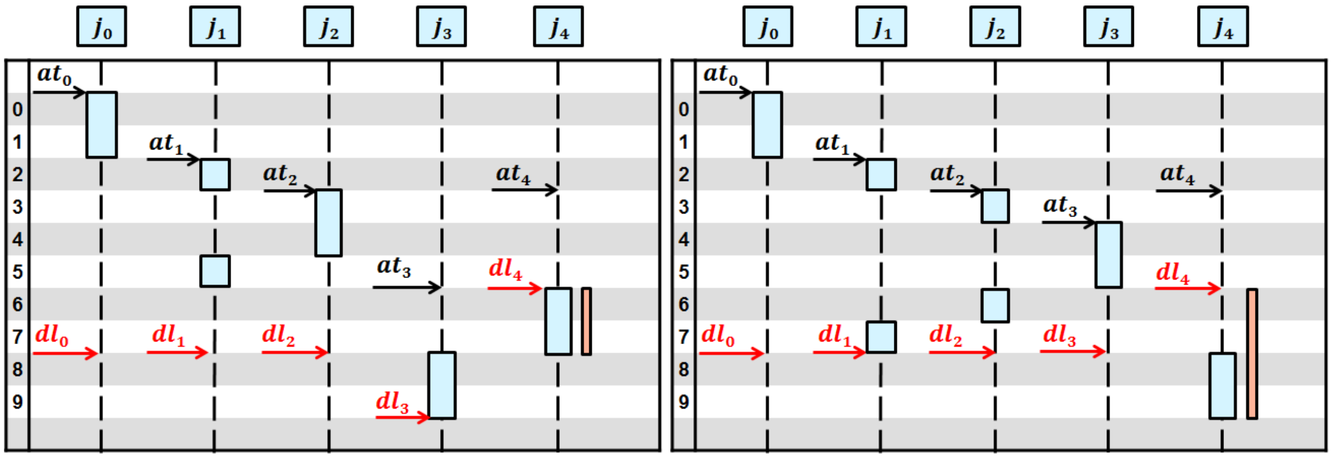
7.1.1 GA+CP in Practice: a Working Example

In this section, we introduce an example to show how GA+CP works in practice. Consider the system composed of five aperiodic tasks detailed in Table 7.1. Note that *pe* and *of* are not defined, since each task is aperiodic. There are also no *tg* relationships between tasks.

Suppose GA finds the solution $x = \Big[[0][2][3][6][3]\Big]$, where each task is executed once, and j_0 arrives at time 0, j_1 at time 2, j_3 at time 3, j_4 at time 6 and j_5 at time 3. The schedule corresponding to this solution is shown in Figure 7.2.1.

	$T = [0,9]$			$c = 1$		
Task	pr	dr	mn	mx	dl	de
j_0	0	2	10	10	8	
j_1	1	2	10	10	6	j_4
j_2	2	2	10	10	5	
j_3	3	2	10	10	4	
j_4	4	2	10	10	3	j_1

Table 7.1. Example system with four tasks and one dependency



(7.2.1) Solution x found by GA (7.2.2) Solution x' found by GA+CP

Figure 7.2. GA+CP neighborhood search example

In x, j_4 misses its deadline by 2 time quanta, being the task that has the biggest deadline miss. Therefore, $J^*(x) = \{j_4\}$. By looking at the tasks priorities and dependencies, j_1 depends on j_4, and both j_2 and j_3 have higher priority than j_1, so all three can potentially have an impact over the execution of j_4 for the reasons detailed in above. This means that $I_{j_4}(x) = \{j_1, j_2, j_3, j_4\}$, and consequently $I^*(x) = \{j_1, j_2, j_3, j_4\}$.

GA+CP searches the space around x up to a distance D from the tasks in $I^*(x)$, i.e., the tasks that can potentially have an impact over the execution of j_4. This local search is performed by solving the CP model $\mathcal{M}'(x)$ derived from $\mathcal{M}$ by specifying that:

- The arrival time of j_0 is fixed, since $j_0 \notin I^*(x)$. This step is done by adding to $\mathcal{M}$ the following constraint: $at(j_0, 0) = 0$. In practice, $at(j_0, 0)$ is declared in $\mathcal{M}'(x)$ as a constant with value 0.
- The arrival times of tasks in $I^*(x)$ are bounded within distance D from the arrival times computed by GA in x. For this example, suppose $D = 2$. This step is done by adding to $\mathcal{M}$ the following

constraints:

$$\begin{aligned}
2-2=0 &\leq at(j_1,0) \leq 4 = 2+2 \\
3-2=1 &\leq at(j_2,0) \leq 5 = 3+2 \\
6-2=4 &\leq at(j_3,0) \leq 8 = 6+2 \\
3-2=1 &\leq at(j_4,0) \leq 5 = 3+2
\end{aligned}$$

In practice, $at(j_1)$ is declared in $\mathcal{M}'(x)$ as a variable with domain $[0,4]$, $at(j_2)$ as a variable with domain $[1,5]$, $at(j_3)$ as a variable with domain $[4,8]$, and $at(j_4)$ as a variable with domain $[1,5]$.

GA+CP solves this model to optimality and finds the solution $x' = \Big[[0][2][3][4][3]\Big]$, with the schedule shown in Figure 7.2.2. In x', j_4 misses its deadline by 4 quanta, and therefore GA+CP has succeeded in improving the solution found by GA by finding a larger deadline miss.

7.2 Validation of GA+CP in Five Subject Systems from Safety-critical Domains

The goal of our empirical study is to compare the overall performance of GA, CP, and GA+CP for the purpose of supporting stress testing of task deadlines. The design of this empirical study is similar to that described in Section 6.2.2, as the comparison is performed on the same five subject systems introduced in Section 6.2.2.1. The goal of our study is to answer the research questions presented in Section 7.2.1. Note that, in addition to the research questions related to efficiency, effectiveness, and scalability introduced in Section 6.2.2.2, we also investigate a fourth property of the search strategies that concerns the capability to exercise the system in a more *diverse* way with respect to task executions. Therefore, we define metrics and attributes in Section 7.2.2 to capture the test cases variety in terms of (1) time span and (2) preemptions between task executions, and (3) number aperiodic task executions. The design of our experiment is described in Section 7.2.3, and its results are discussed in Section 7.2.4. Finally, Section 7.2.5 covers some potential threats that could affect the general validity of our conclusions.

7.2.1 Research Questions

The goal of our empirical study is answering the following research questions involving GA, CP and GA+CP for the purpose of supporting stress testing of task deadlines. Note that RQ1, RQ2, and RQ4 have been introduced in Section 6.2.2.2, and are reported here.

- **RQ1 — Efficiency**. Does one search strategy find the best solutions significantly faster than the other?
- **RQ2 — Effectiveness**. Does one search strategy find significantly better solutions (i.e., solutions with worse deadline misses) than the other?
- **RQ3 — Diversity**. Does one search strategy find solutions that are significantly more diverse (i.e., solutions that exercise the system in a larger number of different ways) than the other?

- **RQ4 — Scalability**. To what extent does the size of a system affect the efficiency of the search strategies?

RQ1, RQ2 and RQ3 are investigated through a set of metrics and attributes detailed in Section 7.2.2. The goal of such metrics and attributes is to provide quantitative evidence to answer the research questions. Similar to Section 6.2.2.5, RQ4 will instead be only qualitatively discussed in Section 7.2.4. Note that we base our analysis of efficiency on a set of five systems, and therefore no quantitative study, for example based on regression analysis, can be carried out to identify precise trends.

7.2.2 Comparison Metrics and Attributes

Similar to Section 6.2.2.3, we broke down the objective function F_{DM} (Section 6.1.4) into several factors of practical interest while investigating worst case scenarios for deadline misses. For this reason, we defined the efficiency and effectiveness, and diversity properties related to RQ1, RQ2, and RQ3 as attributes, and we defined a set of metrics to enable their measurement. Therefore, we compare the performance of GA, CP and GA+CP by collecting data pertaining to the metrics t, s, n, m, and the attributes η and κ defined in Section 6.2.2.3. In addition, we define the attributes related to diversity for each search strategy Γ running during an experiment on the target system Σ. Indeed, an ideal test suite has three main properties:

1. It is computed in the shortest possible time.
2. It contains test cases that are as likely as possible to push tasks to miss their deadlines at runtime.
3. It contains test cases that are as little redundant as possible.

Recall from Section 6.2.2.3 that *efficiency* captures the first property, measuring how quickly a search strategy converges to the optimal solutions it finds, while *effectiveness* captures the second property, measuring how likely are the solutions found to characterize stress cases that will reveal deadline misses at runtime. The third property is instead captured by the concept of *diversity*. Conceptually, diversity among stress test cases is similar to test coverage in functional testing. Indeed, a test suite that yields high coverage with respect to a given criterion ensures that the system will be thoroughly tested with respect to that criterion. Similarly, a test suite that yields high diversity ensures that test cases will thoroughly exercise interactions between task executions.

In general, the higher the number of best solutions of a search strategy, the higher the number of effective test cases it generates. Note that the effectiveness κ is a different concept from the number N of solutions which are effective. Since N does not take into account redundancy among solutions, it is not true in general that the higher N, the more effective a search strategy is. For example, a strategy could generate a large number of effective test cases that yet exercise the system with respect to very similar scenarios. On the other hand, another strategy could generate fewer effective test cases that are instead highly diverse. For this reason, the number of best solutions is only meaningful when considered together with the redundancy of the solutions, formalized by the concept of diversity. Therefore, the number of best solutions relates to RQ3.

Number of best solutions. *We define the number N of best solutions with respect to a given metric* *as the cardinality of the set of best solutions found with respect to that metric. Specifically, we define effectiveness with respect to s, m, and n.*

$$N_s \overset{def}{=} \left|X_s^*\right| \qquad N_n \overset{def}{=} \left|X_n^*\right| \qquad N_m \overset{def}{=} \left|X_m^*\right|$$

We define three types of diversity δ, each with respect to a given metric. Specifically, we define the *shift* diversity δ_h, the *pattern* diversity δ_r, and the *executions* diversity δ_e, each defined with respect to the three metrics s, m, and n. Intuitively, the shift diversity δ_h measures the extent to which solutions exercise the system during time intervals that are distant from each other. Therefore, the diversity attribute relates to RQ3.

The shift diversity is defined based on the shift distance between active vectors, which measures the distance in time between a given execution in two solutions.

Shift Distance between Active Vectors. *Let $A_{j,k}(x)$ and $A_{j,k}(y)$ be the active vectors of task execution (j,k) in the solutions x and y, respectively. We define the shift distance $\mathcal{D}_{h,j,k}(x,y)$ between $A_{j,k}(x)$ and $A_{j,k}(y)$ as the sum of absolute differences between their start and end times.*

$$\mathcal{D}_{h,j,k}(x,y) \overset{def}{=} \left|st_{j,k}(x) - st_{j,k}(y)\right| + \left|en_{j,k}(x) - en_{j,k}(y)\right|$$

For example, in Figures 7.2.1 and 7.2.2, $\mathcal{D}_{h,j_1,0} = |\,2-2\,| + |\,6-8\,| = 2$.

Average Shift Distance between Pairs of Executions. *We define $\mathcal{D}_{h,j}(x,y)$ as the average shift distance over pairs of executions of task j in solutions x and y.*

$$\mathcal{D}_{h,j}(x,y) \overset{def}{=} \frac{\sum\limits_{k\in\left(K_j(x)\cap\in K_j(y)\right)} \mathcal{D}_{h,j,k}(x,y)}{\left|K_j(x)\cap K_j(y)\right|}$$

In Figures 7.2.1 and 7.2.2, $\mathcal{D}_{h,j_1} = \mathcal{D}_{h,j_1,0} = 2$, since j_1 is executed only once.

Shift Diversity between Solutions. *We define $\delta_h\Big(A(x),A(y)\Big)$ as the shift diversity between the solutions x and y as the sum of the shift distances between $A_j(x)$ and $A_j(y)$ for $j \in J$:*

$$\delta_h\Big(A(x),A(y)\Big) \overset{def}{=} \sum_{j\in J} \mathcal{D}_{h,j}(x,y)$$

Shift Diversity between Two Solutions. *We define δ_h as the shift diversity with respect to a given metric as the average shift diversity over the set of best solutions for that metric.*

$$\delta_{h,s} \overset{def}{=} \frac{\sum\limits_{x,y\in X_s^*} \delta_h(x,y)}{|X_s^*|} \qquad \delta_{h,n} \overset{def}{=} \frac{\sum\limits_{x,y\in X_n^*} \delta_h(x,y)}{|X_n^*|} \qquad \delta_{h,m} \overset{def}{=} \frac{\sum\limits_{x,y\in X_m^*} \delta_h(x,y)}{|X_m^*|}$$

In Figures 7.2.1 and 7.2.2, $\delta_h = 0+2+2+8+4 = 16$.

The pattern diversity δ_r measures the extent to which solutions exercise the system such that tasks are preempted at different times. The pattern diversity is defined based on the pattern distance between active vectors, which measures the difference between the preemption times of a given task execution in two solutions.

Pattern Distance between Active Vectors. *Let $A_{j,k}(x)$ and $A_{j,k}(y)$ be the active vectors of task execution (j,k) in the solutions x and y, respectively. We define the pattern distance $\mathcal{D}_{r,j,k}(x,y)$ between $A_{j,k}(x)$ and $A_{j,k}(y)$ as the sum of the absolute differences between the preemption values of task j.*

$$\mathcal{D}_{r,j,k}(x,y) \overset{def}{=} \sum_{p \in P_j \setminus \{0\}} \left| pm_{j,k,p}(x) - pm_{j,k,p}(y) \right|$$

For example, in Figures 7.2.1 and 7.2.2, $\mathcal{D}_{r,j_2,0} = |\ 0-2\ | = 2$.

Average Pattern Distance between Pairs of Executions. *We define $\mathcal{D}_{r,j}(x,y)$ as the average shift distance over pairs of executions of task j in solutions x and y.*

$$\mathcal{D}_{r,j}(x,y) \overset{def}{=} \frac{\sum\limits_{k \in \left(K_j(x) \cap \in K_j(y)\right)} \mathcal{D}_{r,j,k}(x,y)}{\left|K_j(x) \cap K_j(y)\right|}$$

In Figures 7.2.1 and 7.2.2, $\mathcal{D}_{r,j_2} = \mathcal{D}_{r,j_2,0} = 2$, since j_2 is executed only once.

Pattern Diversity between Two Solutions. *We define $\delta_r\left(A(x),A(y)\right)$ as the diversity between the solutions x and y, i.e., as the sum of the pattern distances between $A_j(x)$ and $A_j(y)$ for $j \in J$.*

$$\delta_r\left(A(x),A(y)\right) \overset{def}{=} \sum_{j \in J} \mathcal{D}_{r,j}(x,y)$$

Pattern Diversity. *We define the pattern diversity δ_r with respect to a given metric as the average pattern diversity over the set of best solutions for that metric.*

$$\delta_{r,s} \overset{def}{=} \frac{\sum\limits_{x,y \in X_s^*} \delta_r(x,y)}{|X_s^*|} \qquad \delta_{r,n} \overset{def}{=} \frac{\sum\limits_{x,y \in X_n^*} \delta_r(x,y)}{|X_n^*|} \qquad \delta_{r,m} \overset{def}{=} \frac{\sum\limits_{x,y \in X_m^*} \delta_r(x,y)}{|X_m^*|}$$

In Figures 7.2.1 and 7.2.2, $\delta_r = 0+2+2+0+0 = 4$.

The execution diversity δ_e measures the extent to which solutions exercise the system such that tasks are executed different numbers of times.

Execution Diversity between Two Solutions. *We define $\delta_e\Big(A(x),A(y)\Big)$ as the execution diversity between the solutions x and y, i.e., as the sum of the absolute differences between the number of task executions in solutions x and y.*

$$\delta_e\Big(A(x),A(y)\Big) \overset{def}{=} \sum_{j\in J}\Big||K_j(x)| - |K_j(y)|\Big|$$

Execution Diversity. *We define δ_h as the execution diversity with respect to a given metric, i.e., as the average execution diversity over the set of best solutions for that metric.*

$$\delta_{e,s} \overset{def}{=} \frac{\sum_{x,y\in X_s^*} \delta_e(x,y)}{|X_s^*|} \qquad \delta_{e,n} \overset{def}{=} \frac{\sum_{x,y\in X_n^*} \delta_e(x,y)}{|X_n^*|} \qquad \delta_{e,m} \overset{def}{=} \frac{\sum_{x,y\in X_m^*} \delta_e(x,y)}{|X_m^*|}$$

For example, in Figures 7.2.1 and 7.2.2, $\delta_e = \mid 1-1 \mid + \mid 1-1 \mid + \mid 1-1 \mid + \mid 1-1 \mid + \mid 1-1 \mid = 0$ because each task gets executed once in each solution.

7.2.2.1 Diversity Properties

We note that δ_h, δ_r, and δ_e are defined as non-negative, symmetric, and subadditive. Furthermore, when considered in conjunction, the three diversities also satisfy the coincidence property. Specifically, δ_h, δ_r, and δ_e satisfy the following four properties.

1. **Non-Negativity**
$$\forall x,y \cdot \delta_h(x,y) \geq 0 \land \delta_r(x,y) \geq 0 \land \delta_e(x,y) \geq 0$$
2. **Coincidence**
$$\forall x,y \cdot \delta_h(x,y) = 0 \land \delta_r(x,y) = 0 \land \delta_e(x,y) = 0 \iff x = y$$
3. **Symmetry**
$$\forall x,y \cdot \delta_h(x,y) = \delta_h(y,x) \land \delta_r(x,y) = \delta_r(y,x) \land \delta_e(x,y) = \delta_e(y,x)$$
4. **Subadditivity (Triangle inequality)**
$$\begin{aligned}\forall x,y,z \cdot \delta_h(x,y) + \delta_h(y,z) &\geq \delta_h(x,z) \land \\ \delta_r(x,y) + \delta_r(y,z) &\geq \delta_r(x,z) \land \\ \delta_e(x,y) + \delta_e(y,z) &\geq \delta_e(x,z)\end{aligned}$$

The proofs of the above four properties are straightforward and follow from the definition of δ_h, δ_r, and δ_e as sums of absolute values. These properties enable the definition of the three types of diversity as distance functions on the set of solutions.

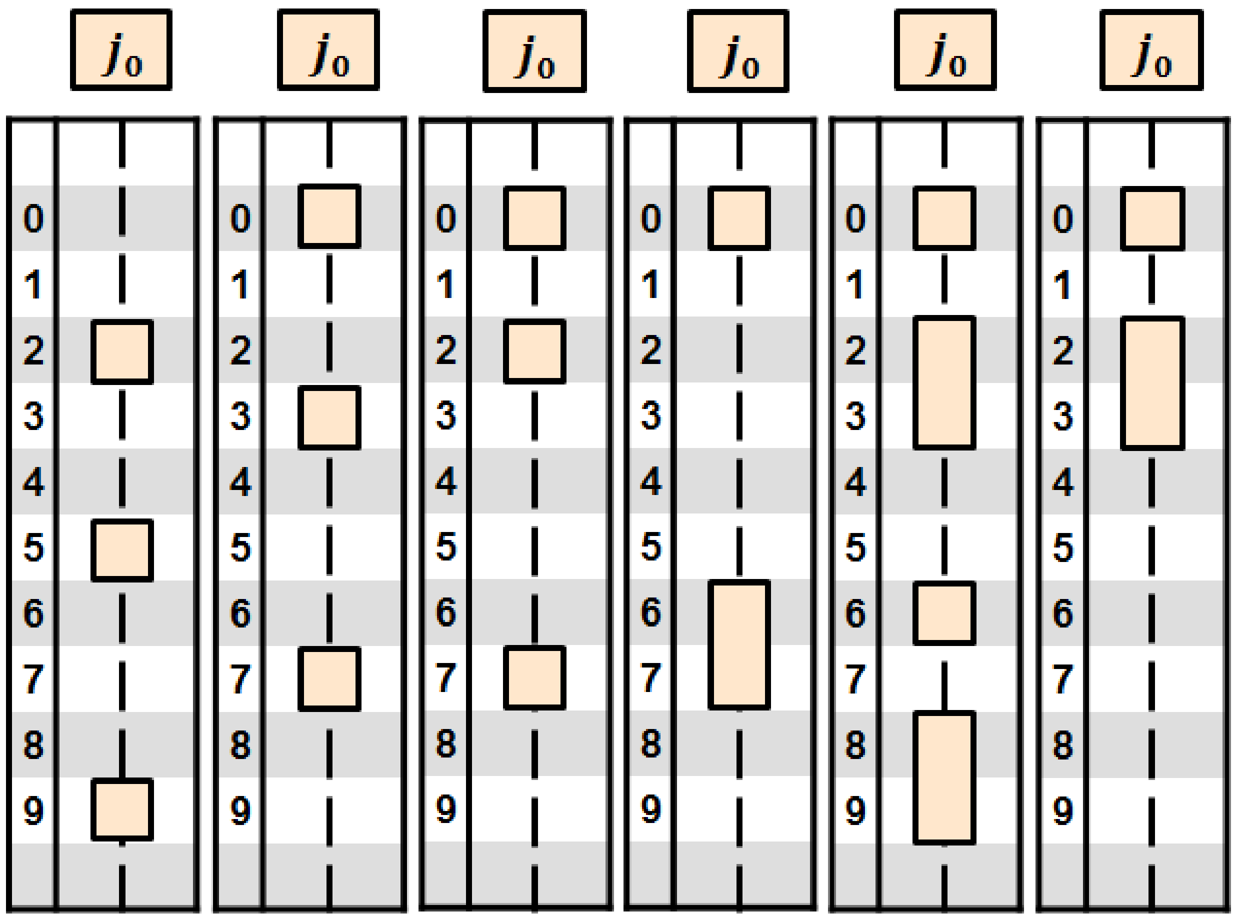
7.2.2.2 Diversity Examples

In this section, we present an example with three pairs of solutions x and y. Each pair represent a case where only one type of diversity, δ_h, δ_r, and δ_e respectively, has a non-zero value. This highlights the necessity of breaking down the concept of diversity into three orthogonal sub-attributes that have to be considered together when analyzing how differently stress test cases exercise the system.

Consider the single-task system detailed in Table 7.2. Note that *pe* and *of* are not defined, since j_0 is aperiodic. Trivially, there are also no *de* and *tg* relationships.

	$T=[0,9]$			$c=1$	
Task	*pr*	*dr*	*mn*	*mx*	*dl*
j_0	0	3	4	10	6

Table 7.2. Example system with one task



(7.3.1) x_1 (7.3.2) y_1 (7.3.3) x_2 (7.3.4) y_2 (7.3.5) x_3 (7.3.6) y_3

Figure 7.3. Six example solutions for the system in Table 7.2

Figure 7.3 shows six different solutions for the system detailed in Table 7.2. In their schedules, we omitted the arrival times and deadlines of j_0, since they are not relevant for the definition of diversity. Note that j_0 is the only task of the system, and therefore it cannot be preempted. However, in these example solutions, we introduce unnecessary task preemptions to meaningfully describe the concept of diversity.

Consider the two solutions x_1 and y_1 in Figures 7.3.1 and 7.3.2. In this case, we note that $\delta_h(x_1, y_1) = \mid 2-0 \mid + \mid 9-7 \mid = 4$. This reflects the fact that x_1 is predicted to exercise the system in the interval $[2,9]$, and y_1 is predicted to do so in $[0,7]$. Furthermore, $\delta_r(x_1, y_1) = \mid 3-3 \mid + \mid 4-4 \mid = 0$. This reflects the fact that in both x_1 and y_2 task j_0 is predicted to preempt at runtime in the same way, i.e., by two time quanta the first time, and by three the second time. Finally, $\delta_e(x_1, y_1) = \mid 1-1 \mid = 0$ since in both solutions j_0 gets executed once.

Furthermore, consider the two solutions x_2 and y_2 in Figures 7.3.3 and 7.3.4. In this case, we note that $\delta_h(x_2, y_2) = \mid 0-0 \mid + \mid 7-7 \mid = 0$. This reflects the fact that x_2 and y_2 are both predicted to exercise the system in the same interval $[0,7]$. However, $\delta_r(x_2, y_2) = \mid 1-5 \mid + \mid 4-0 \mid = 8$. This reflects the fact that in x_2 and y_2 task j_0 is predicted to preempt at runtime in different ways. Indeed, j_0 is preempted twice for one and four time quanta in x_3, while in y_2 it is preempted once for five time quanta. Finally, $\delta_e(x_2, y_2) = \mid 1-1 \mid = 0$ since even in this case j_0 gets executed once in both solutions.

Finally, consider the two solutions x_3 and y_3 in Figures 7.3.5 and 7.3.6. In this case, we note that $\delta_h(x_3, y_3) = \mid 0-0 \mid + \mid 3-3 \mid = 0$. This reflects the fact that, considering only the first execution of j_0 that is present in both solutions, x_3 and y_3 are predicted to exercise the system in the same interval $[0,4]$. Moreover, $\delta_r(x_3, y_3) = \mid 1-1 \mid + \mid 0-0 \mid = 0$. This reflects the fact that, considering again the only common execution of j_0, x_3 and y_3 are both predicted to preempt j_0 once by one time quanta. However, $\delta_e(x_3, y_3) = \mid 2-1 \mid = 1$ since in this case j_0 gets executed twice in x_3 and only once in y_3.

7.2.3 Experiments Set-Up

To answer the research questions, we performed a series of experiments over the systems described in Section 6.2.2.1. The experimental design is illustrated in Figure 7.4. Each experiment consisted of running GA, CP and GA+CP on a target system Σ for a number of times, each run generating a set X of solutions. Since the purpose of our empirical study is to compare the practical usefulness of the three strategies and give an insight over their scalability, we chose to run them in the way engineers would realistically do so in a real testing environment. Based on our experience with industrial partners, we assumed that a reasonable choice would be running GA and CP for ten hours. Note that this interval is sensibly longer than the one hour time budget we adopted while initially validating CP (Section 6.2.2.4). We set up GA to continuously generate new solutions for ten hours, while we set up CP to terminate the search after ten hours. GA+CP was instead run by performing one local CP search for each solution found by GA. We set a timeout of 2 hours for these local searches, so that GA+CP was run for a total of 12 hours. However, note that CP terminates the search upon proof of optimality. Since CP performed the local searches in a significantly small subset of the search space (recall Figure 7.1), the local CP searches always terminated with proof of optimality before the 2 hours timeout. Therefore, even if we instructed GA+CP to run longer than GA and CP, the time taken by CP to terminate the local searches was practically not significant with respect to the 10 hours taken by GA to generate its solutions. For each run of GA, CP, and GA+CP, we recorded in X only the 100 solutions with the highest fitness/objective value found. As explained in Section 6.2.2.4, this is because each solution characterizes a stress test case, and 100 has proven to be a satisfactory number of observations to meaningfully compare two distributions [Arcuri and Briand, 2011]. Similar to GA and CP, we instructed GA+CP to run 100 CP searches as described in Section 7.1 each in the neighborhood of a solution found by GA.

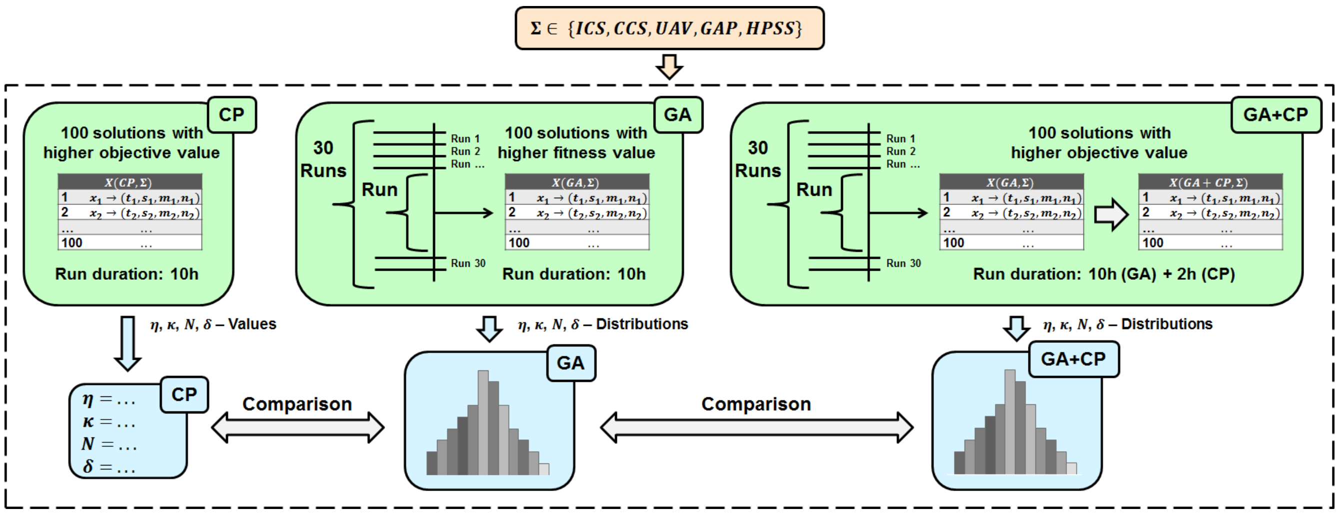

$\Sigma \in \{ICS, CCS, UAV, GAP, HPSS\}$
CP
100 solutions with higher objective value
$X(CP,\Sigma)$
1 $x_1 \rightarrow (t_1, s_1, m_1, n_1)$
2 $x_2 \rightarrow (t_2, s_2, m_2, n_2)$
100
Run duration: 10h
GA
30 Runs
Run
Run 1
Run 2
Run ...
Run 30
100 solutions with higher fitness value
$X(GA,\Sigma)$
Run duration: 10h
GA+CP
100 solutions with higher objective value
$X(GA+CP,\Sigma)$
Run duration: 10h (GA) + 2h (CP)
η, κ, N, δ – Values
η, κ, N, δ – Distributions
$\eta = \dots$
$\kappa = \dots$
$N = \dots$
$\delta = \dots$
Comparison
Comparison

Figure 7.4. Experimental design: we run CP a single time recording the 100 solutions with highest objective value, and calculating a single value for each metric. Then, we run GA and GA+CP 30 times recording the 100 solutions with highest fitness value, and calculating distributions for the metrics.

Running the three search strategies for approximately the same amount of time allows us to meaningfully compare effectiveness, number of solutions found, and diversity. Furthermore, during the design of the experiment, we had to consider the inherent randomized behavior of GA in contrast to the full determinism of CP. Indeed, GA finds solutions starting from a randomly chosen initial population of individuals by applying crossover and mutation operators with a given probability, while CP finds solutions by solving a constraint optimization problem. For this reason, while we ran CP only once for each system, we ran GA, and consequently GA+CP 30 times on each system. In this way, we could compute the comparison metrics distributions of the best solutions recorded over 30 runs. Since our research questions are directly related to attributes η, κ, N, and δ, for each solution $x \in X$ we computed the values of the metrics t, s, n, and m used to define such attributes. GA, CP and GA+CP runs have been separately executed on a single AMAZON EC2 M2.XLARGE[1] instance.

7.2.4 Results and Discussion

In this section, we discuss the experimental results for the attributes η, κ, N, and δ in each subject system. Each attribute is discussed through 15 box-and-whisker plots, one for each pair of metric and

[1] http://aws.amazon.com

system. In each plot, the x-axis reports the search strategies CP, GA, and GA+CP, denoted as C, G, and + respectively. The y-axis reports instead the value for the comparison attribute. Each plot is also complemented by two p-values from the non-parametric Wilcoxon statistical significance test between GA+CP and CP (first row), and between GA+CP and GA (second row). Specifically, we report the p-values from the Wilcoxon rank-sum test for the difference between GA+CP and GA, and the Wilcoxon signed-rank test for the difference between GA+CP and CP. The former is a two-sample test comparing two distributions, while the latter is a one-sample test, given the deterministic nature of CP. In particular, we investigated the statistical significance of differences between CP and GA/GA+CP by testing the null hypothesis that the median of the GA/GA+CP distributions are the deterministic values obtained with CP. For all tests, we selected a level of significance $\alpha = 0.05$. Note that a centered dot $(\cdot)$ in place of a Wilcoxon test p-value indicates that the test has not been performed. This happens when the two distributions considered for the test are identical, and hence the effective sample size, i.e., the number of observation pairs with different values, is zero.

7.2.4.1 RQ1 — Efficiency

The first three columns in Table 7.3 report the efficiency η with respect to s, n and m for GA+CP, GA, and CP, and for each subject system. The computation times for the best solutions are reported in the format *hh:mm*. We observe how, on each system, GA+CP has a worse efficiency than GA with respect to each metric. With the exclusion of η_n for ICS and UAV, the difference in efficiency is also statistically significant as shown by the p-values below 0.05. This result is expected because GA+CP performs a complete search in the neighborhood of GA solutions, and therefore, the time GA+CP requires to find its best solution is in general higher than that of GA. However, the difference between the average efficiency of GA+CP and GA is small from a practical standpoint, and does not keep GA+CP from being far more efficient than CP. Specifically, the difference between the η_s, η_n and η_m medians of GA and GA+CP vary from around 20 minutes in ICS (Tables 7.3.1 to 7.3.3) up to 1.5 hour in HPSS (Tables 7.3.37 to 7.3.39). This difference has little practical significance when compared to the ten hours duration of each run, and to the efficiency of CP, that varies from 3.5 hours in ICS up to almost ten hours in HPSS. The statistical significance of the difference between the efficiency of GA+CP and CP is also reflected in the p-value for the signed-rank test, which is below 0.0001 for each metric and subject system. On average, the results show that GA+CP is twice as fast than CP but only 20% slower than GA in finding the best solutions x_s^*, x_n^*, and x_m^*.

7.2.4.2 RQ2 — Effectiveness

The second three columns in Table 7.3 reports the effectiveness κ with respect to s, n and m for GA+CP, GA, and CP, and for each subject system. We observe how, on each system, GA+CP has equal or greater effectiveness than that of GA with respect to each metric. This result is also expected, since GA+CP performs a complete search in the neighborhood of GA solutions, and thus the solutions it finds are always equal or better than those of GA. We note how GA+CP is significantly more effective than GA for two out of three metrics in most of the subject systems, being so for all the three metrics in GAP and HPSS. Moreover, for n and m, GA+CP also achieves nearly the same effectiveness as CP in most of the subject systems. In particular, in ICS, CCS and UAV, GA+CP achieves the same value as CP for κ_n in

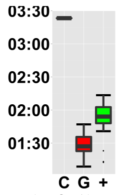
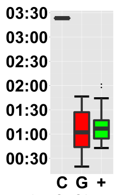
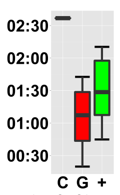
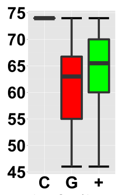
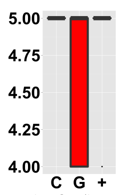
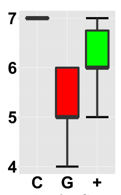
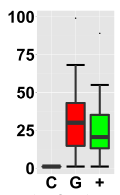
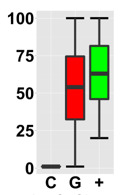
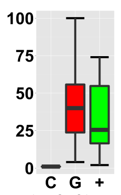
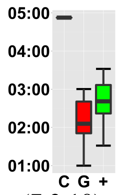
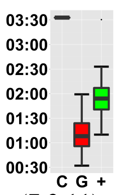
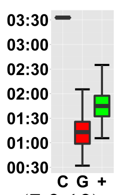
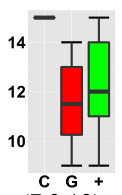
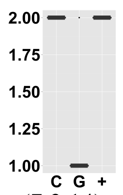
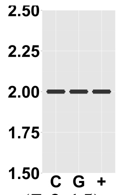
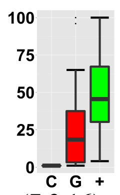
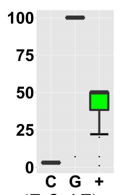
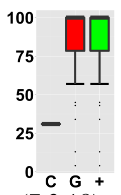
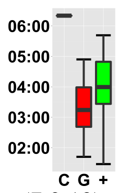
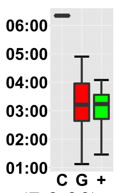
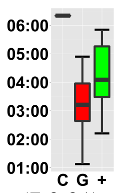
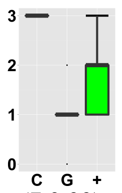
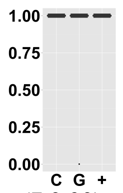
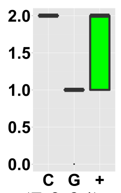
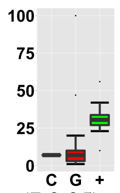
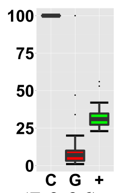
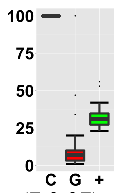
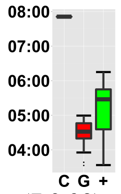
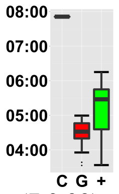
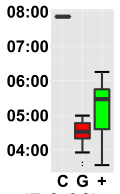
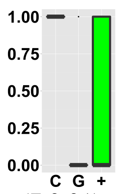
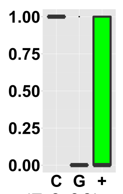
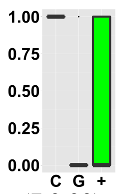
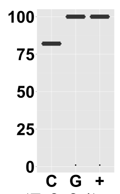
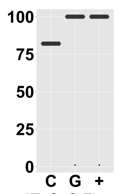
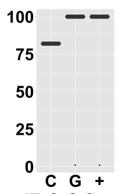
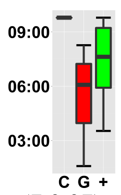
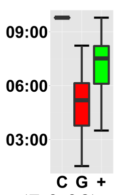
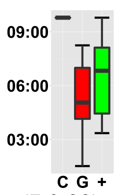
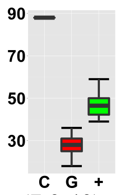
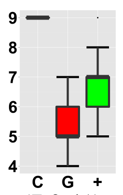
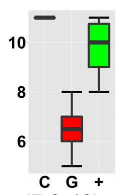
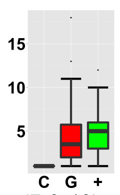
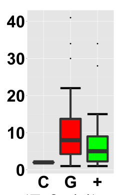
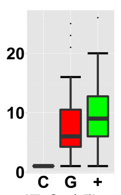
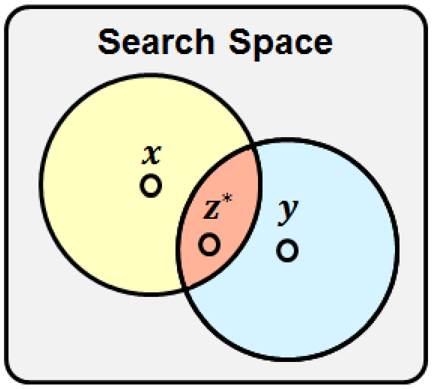
	η_s	η_n	η_m	κ_s	κ_n	κ_m	N_s	N_n	N_m
ICS	 (7.3.1) $<.0001$ $<.0001$	 (7.3.2) $<.0001$ .3403	 (7.3.3) $<.0001$ .0026	 (7.3.4) $<.0001$ .0730	 (7.3.5) $<.3256$ .0062	 (7.3.6) $<.0001$ $<.0001$	 (7.3.7) $<.0001$ .2640	 (7.3.8) $<.0001$ .1932	 (7.3.9) $<.0001$ .1784
CCS	 (7.3.10) $<.0001$ $<.0016$	 (7.3.11) $<.0001$ .0001	 (7.3.12) $<.0001$ .0001	 (7.3.13) $<.0001$ .1996	 (7.3.14) · .0001	 (7.3.15) · ·	 (7.3.16) $<.0001$ .1996	 (7.3.17) $<.0001$ .0001	 (7.3.18) $<.0001$ ·
UAV	 (7.3.19) $<.0001$ .0133	 (7.3.20) $<.0001$ .6309	 (7.3.21) $<.0001$ .0013	 (7.3.22) $<.0001$ $<.0001$	 (7.3.23) · .3337	 (7.3.24) .0005 $<.0001$	 (7.3.25) $<.0001$ $<.0001$	 (7.3.26) $<.0001$ $<.0001$	 (7.3.27) $<.0001$ $<.0001$
GAP	 (7.3.28) $<.0001$ .0009	 (7.3.29) $<.0001$ .0009	 (7.3.30) $<.0001$ .0009	 (7.3.31) $<.0001$ .0062	 (7.3.32) $<.0001$ .0062	 (7.3.33) $<.0001$ .0062	 (7.3.34) .5171 .0246	 (7.3.35) .5171 .0246	 (7.3.36) .5171 .0246
HPSS	 (7.3.37) $<.0001$ .0015	 (7.3.38) $<.0001$ .0003	 (7.3.39) $<.0001$ .0420	 (7.3.40) $<.0001$ $<.0001$	 (7.3.41) $<.0001$ $<.0001$	 (7.3.42) $<.0001$ $<.0001$	 (7.3.43) $<.0001$ .2215	 (7.3.44) .0004 .0605	 (7.3.45) $<.0001$ .1324

Table 7.3. Experimental results of CP (C), GA (G), and GA+CP (+) for efficiency η, effectiveness κ, and number N of best solutions. Each box-and-whisker plot reports at the bottom the Wilcoxon test p-values between GA+CP and CP (first value), and between GA+CP and GA (second value).

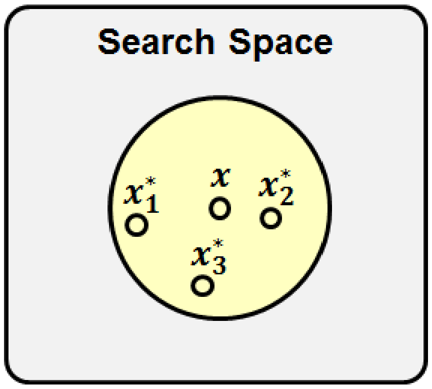
the first quartile (Tables 7.3.5, 7.3.14 and 7.3.23), and for κ_m in the second quartile (Tables 7.3.6, 7.3.15 and 7.3.24). On the other hand, in these three subject systems, GA achieves the same effectiveness as CP on the second or third quartile on average. Note that, in CCS and UAV, GA never achieves the same effectiveness as CP for the criteria n and m. In GAP, GA+CP achieves the same effectiveness as CP in the third quartile for all the three criteria, identifying a deadline miss in one third of the runs (Tables 7.3.31 to 7.3.33). In comparison, GA found a deadline miss only in a single run. Finally, in HPSS, GA+CP does not match the effectiveness of CP, but significantly improves the results of GA, having a first quartile that is around 30% larger than that of GA for s and m (Tables 7.3.40 and 7.3.42). Finally, we note that, with the exception of κ_s for ICS and CCS, whenever there is a statistically significant, positive difference in the effectiveness between CP and GA+CP, there is also one between GA+CP and GA. On average, the results show that GA+CP is significantly more effective than GA, and is approaching CP in finding the best solutions x_n^* and x_m^*.

7.2.4.3 RQ3 — Diversity

The last three columns in Table 7.3 reports the number N of best solutions with respect to s, n and m for GA+CP, GA, and CP, and for each subject system. We observe how, on most systems, the number of best solutions found by GA+CP is similar to that of GA, even though it is not consistently larger or smaller. We conjecture that the reason for this result stems from the way GA+CP is designed to improve the solutions found by GA. Consider the scenarios shown in Figure 7.5.



(7.5.1) Two or more solutions share the same local optimum in their neighborhoods



(7.5.2) There is more than one local optimum in the neighborhood of a solution

Figure 7.5. Different scenarios of how GA+CP affects the number N of best solutions

Suppose that GA finds two distinct best solutions with respect to a metric, namely x and y. It could be the case that the best solution in the neighborhoods of x and y is the solution z^* . In this case, the number N of best solutions found by GA+CP is smaller than that of GA, because $N(\text{GA}) = 2$, and $N(\text{GA+CP}) = 1$ (Figure 7.5.1). Suppose now that GA finds only a single best solution x with respect to a metric. It could be the case instead, that there is more than a single best solution in the neighborhood of x, namely x_1^*, x_2^*, and x_3^*. In this scenario, the number N of best solutions found by GA+CP is larger than that of GA, because $N(\text{GA}) = 1$, and $N(\text{GA+CP}) = 3$ (Figure 7.5.2). In general, the two scenarios can happen independently from other factors since they depend only on the specific solutions found by GA in a subject system. For this reason, there is no clear trend on whether GA+CP finds a larger or smaller number of best solutions than GA with respect to a metric, as shown by the p-values. We note that, with the exception of GAP and UAV for N_n and N_m (Tables 7.3.26 and 7.3.27), GA and GA+CP find a significantly larger number of best solutions than CP. Note that in ICS, CP finds only a single best solution with respect to s, n, and m (Tables 7.3.7 to 7.3.9), and does so for s and m in HPSS (Tables 7.3.43 and 7.3.45), and for s in CCS (Table 7.3.16). This result is expected because of the randomized nature of GA, and consequently of GA+CP. Indeed, GA finds its solutions by starting from a randomly selected initial population of 80 individuals [Briand et al., 2006] and in our experiment we set up GA to continuously generate and evaluate solutions for ten hours. Even in cases where no deadline misses are revealed, GA is likely to generate a large set of solutions from the initial population. On the other hand, CP is designed to find solutions from scratch with a *branch-and-bound* search process that progressively assigns values to variables in order to satisfy constraints [Apt, 2003]. Furthermore, CP discards by design solutions that have worse objective values than the current best known solution [Atamtürk and Savelsbergh, 2005], and is thus less likely to generate a large set of solutions. Recall that, in our analysis, each solution characterizes a stress test case. Therefore, a large number of solutions is indicative of the size of test suite generated by the search strategies. However, we note that N itself is not sufficient by itself to give a practical measure for the test suite dimension, because many of the solutions found could be redundant (Section 7.2.2). For this reason, the number N of best solutions needs to be considered together with their diversity.

Table 7.4 reports the diversity δ_h, δ_r, and δ_e with respect to s, n and m for GA+CP, GA, and CP, and for each subject system. We observe that, on each system, the three diversities of GA+CP are similar to those of GA, even though they are not consistently larger or smaller. We conjecture that the reason why GA+CP retains a number N of best solutions similar to GA also explains this result. This means that the local search performed by CP in the neighborhood of solutions computed by GA had no significant effect over the three types of diversity in our experiment. Therefore, in our subject systems, the solutions found by GA+CP retained a diversity similar to that of GA. Note that, as expected, in the cases where CP found only a single best solution with respect to a metric, the three diversities have a null value. In GAP, CP found 82 best solutions with respect to s, n, and m, as opposed to 100 for GA and GA+CP. However, the solutions found by GA and GA+CP are far less redundant than those of CP, having a significantly higher shift, pattern, and execution diversity (Tables 7.4.28 to 7.4.36). The same also holds for the criterion s in UAV (Tables 7.4.19, 7.4.22 and 7.4.25), where the three search strategies found 100 best solutions. We finally remark that the diversity is not normalized, and the values are only meant to be compared within the same subject system and the same type of diversity. Recall from Section 7.2.2 that δ_h is defined in terms of start and end times of task executions, and depends mostly on the observation interval T. δ_r is defined in terms of preemptions between task executions, and depends mostly on the task durations. Finally, δ_e is defined in terms of number of task executions, and depends mostly on the ratio between T and the minimum and maximum inter-arrival times of aperiodic tasks. Since T is usually much larger than tasks durations, δ_h has higher values than δ_r and δ_e. For example, in ICS, the average value for $\delta_{h,s}(\text{GA+CP})$ is 83.43. This means that on average, the task executions in the best solutions with respect to s found by GA+CP are shifted by 83.43 time quanta. Similarly, in ICS the average for $\delta_{r,s}(\text{GA+CP})$ is 41.08, meaning that the preemptions between task executions in the best solutions with respect to s found by GA+CP differ on average by 41.08 time quanta. Finally, in ICS the average for $\delta_{e,s}(\text{GA+CP})$ is 1.56,

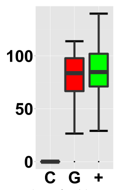
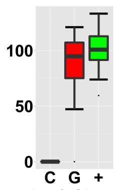
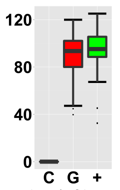
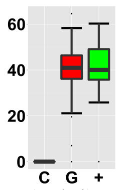
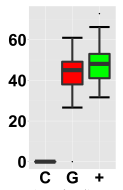
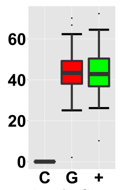
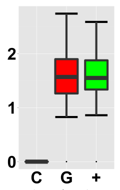
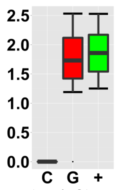
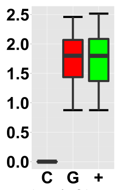
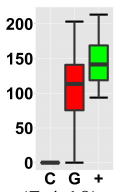
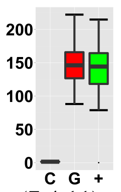
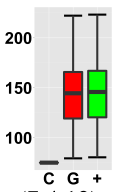
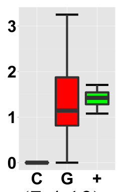
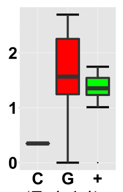
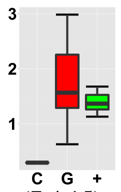
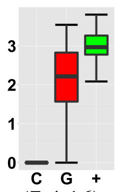
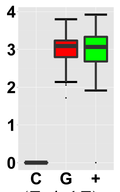
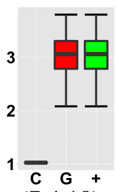
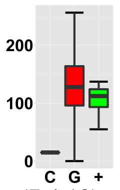
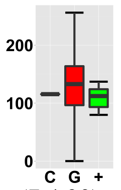
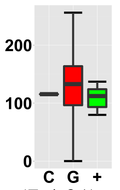
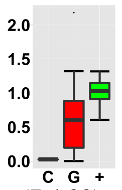
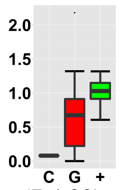
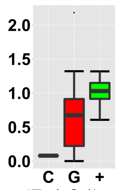
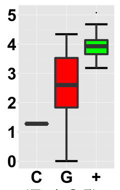
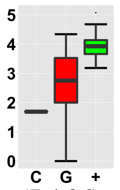
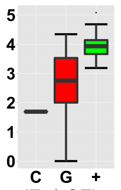
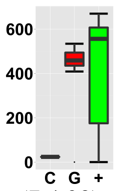
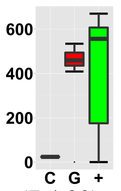
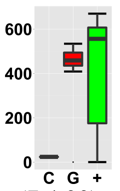
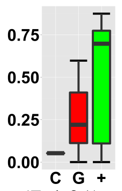
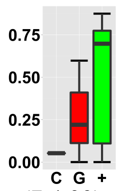
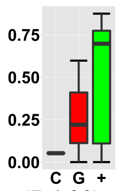
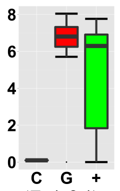
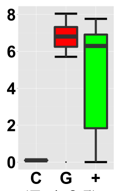
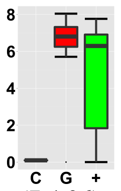
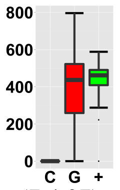
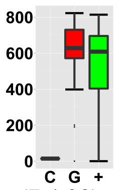
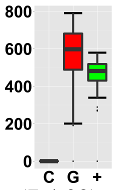
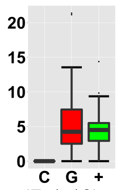
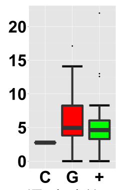
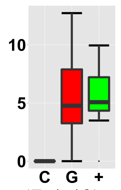
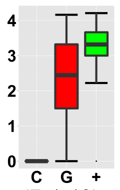
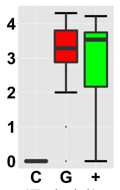
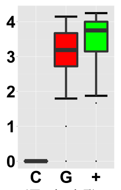
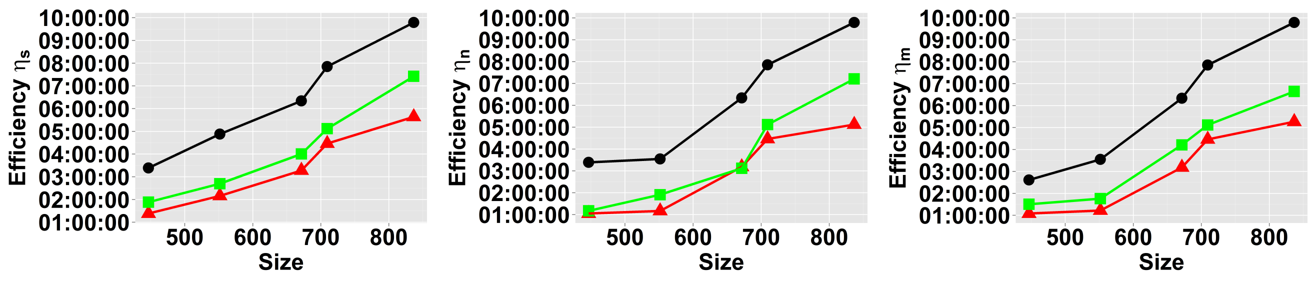
	$\delta_{h,s}$	$\delta_{h,n}$	$\delta_{h,m}$	$\delta_{r,s}$	$\delta_{r,n}$	$\delta_{r,m}$	$\delta_{e,s}$	$\delta_{e,n}$	$\delta_{e,m}$
ICS	 (7.4.1) $< .0001$ .4289	 (7.4.2) $< .0001$ .0406	 (7.4.3) $< .0001$ .5493	 (7.4.4) $< .0001$ .7958	 (7.4.5) $< .0001$ .1154	 (7.4.6) $< .0001$ .9705	 (7.4.7) $< .0001$ .9176	 (7.4.8) $< .0001$ .4688	 (7.4.9) $< .0001$ .8650
CCS	 (7.4.10) $< .0001$ .0070	 (7.4.11) $< .0001$ .7394	 (7.4.12) $< .0001$ .7283	 (7.4.13) $< .0001$ .0536	 (7.4.14) $< .0001$ .0948	 (7.4.15) $< .0001$ .1297	 (7.4.16) $< .0001$ .0003	 (7.4.17) $< .0001$ .9352	 (7.4.18) $< .0001$ 1
UAV	 (7.4.19) $< .0001$ .2061	 (7.4.20) .0761 .1087	 (7.4.21) .0761 .1087	 (7.4.22) $< .0001$ $< .0001$	 (7.4.23) $< .0001$ .0002	 (7.4.24) $< .0001$ .0002	 (7.4.25) $< .0001$ $< .0001$	 (7.4.26) $< .0001$ $< .0001$	 (7.4.27) $< .0001$ $< .0001$
GAP	 (7.4.28) $< .0001$ .0021	 (7.4.29) $< .0001$ .0021	 (7.4.30) $< .0001$ .0021	 (7.4.31) $< .0001$ .0034	 (7.4.32) $< .0001$ .0034	 (7.4.33) $< .0001$ .0034	 (7.4.34) $< .0001$ .0913	 (7.4.35) $< .0001$ .0913	 (7.4.36) $< .0001$ .0913
HPSS	 (7.4.37) $< .0001$ .8071	 (7.4.38) $< .0001$ .3147	 (7.4.39) $< .0001$ .0004	 (7.4.40) $< .0001$ .9410	 (7.4.41) $< .0001$ .4597	 (7.4.42) .0004 .5692	 (7.4.43) $< .0001$ .0075	 (7.4.44) $< .0001$ .7061	 (7.4.45) $< .0001$ .0314

Table 7.4. Experimental results of CP (C), GA (G), and GA+CP (+) for diversity δ_h, δ_r, and δ_e. Each box-and-whisker plot reports at the bottom the Wilcoxon test p-values between GA+CP and CP (first value), and between GA+CP and GA (second value).

meaning that on average the tasks in the best solutions with respect to s differ by 1.56 executions.

7.2.4.4 RQ4 — Scalability

Figure 7.6 reports the trend of the efficiency η with respect to the system size for GA+CP (downward triangle), GA (full dot), and CP (diamond). In each graph, the x-axis represents the system size, while the y-axis reports the efficiency of the search strategies. Since we have a set of five subject systems, we did not perform any statistical analysis, and we only limit ourselves to a qualitative discussion. However, for the three criteria the efficiency of GA+CP seems to scale linearly with system size. Indeed, since we represent the size as a logarithm (Section 6.2.2.1), the x-axis in the three graphs has a logarithmic scale, while the y-axis has the usual linear scale. For this reason, the apparently exponential shape of the efficiency trend is in practice linear. Such results are encouraging as they suggest that GA+CP is more to scale to large systems, and therefore be an advantageous solution given its practical trade-off between efficiency, effectiveness and diversity. In particular, note that, even if in HPSS the difference in efficiency between GA+CP and GA is larger than in the other subject systems, to this decrease in efficiency corresponds a significant increase in effectiveness, as discussed before. Finally, we remark that we did not investigate the trend for κ, N, and δ with respect to system size. This is because, unlike η, these last three properties depend most on the specific problem being solved, rather than on its size. For example, there could be very large subject systems with few tasks missing their deadlines, and very small systems where more deadline misses are revealed.



(7.6.1) η_s versus size (7.6.2) η_n versus size (7.6.3) η_m versus size

Figure 7.6. Experimental results for efficiency η versus system size, comparing GA (▲), CP (●), and GA+CP (■)

7.2.4.5 Summary and Discussion

In light of these results, we conclude that, for the subject systems in our experiment, GA+CP has been nearly as efficient as GA and practically as effective as CP, while also generating solutions with a diversity similar to that of GA. Therefore, our results show that, within the range covered by our subject systems, GA+CP retains the advantages of both the efficiency and diversity of GA and the effectiveness of CP.

We conjecture that the reason for this result stems from the three factors discussed above. First, GA+CP is designed to perform a complete local search in the neighborhood of the best solutions computed by GA. Since GA+CP performs an additional search step over GA, it is expected that GA+CP requires more time than GA to find its best solutions. However, since the search performed during the

CP step is confined in a neighborhood of restricted size, such local search is likely to terminate within a short time. Therefore, the time that CP spends improving the solutions found by GA is likely to have a negligible impact when compared to the time required by GA to find them. This allows GA+CP to achieve an efficiency which is only slightly worse than that of GA. Second, the search CP performs in the neighborhood of GA solutions is complete. Therefore, CP is certain to either find the best solution within distance D from the one GA computed, or to terminate proving that the solution found by GA is the best in its neighborhood. Furthermore, the search heuristics detailed in our previous work [Di Alesio et al., 2013] further improve the CP speed in optimizing the GA solutions. We performed a series of experiments on all subject systems varying the neighborhood size D, and empirically found out that a value of $D = 5$ was sufficient for GA+CP to achieve the same effectiveness as CP. However, we note that on different subject systems, CP might need to explore a larger neighborhood of GA solutions to reach the effectiveness of CP, and exploring such larger space might lead to a lower efficiency. Third, GA+CP is designed to search in the neighborhood of solutions computed by GA. This means that the local search performed by CP can find the same local optimum for different GA solutions (Figure 7.5.1), or more than one local optimum for a single GA solution (Figure 7.5.2). However, in our experiments these two scenarios did not have a significant impact on the diversity of solutions identified by GA, and resulted in GA+CP retaining the same diversity as GA.

7.2.5 Threats to Validity

We identified three main threats that could affect the general validity of our conclusions. First, the analysis of efficiency, effectiveness, diversity, and scalability is based on a set of five subject systems. Although evaluating GA+CP with respect to GA and CP in a larger number of systems would have mitigated this threat, the systems have been selected from different RTES domains and vary in size and complexity.

Second, the size of the subject systems selected varies from 6 to 32 tasks, 3 to 9 of which are aperiodic. There could be much larger systems featuring hundreds of tasks, and for those the efficiency and effectiveness of GA+CP need to be investigated. This means that the conclusions drawn are valid only for systems in the same size range of the subject systems used in the comparison. To mitigate these first two threats, we could have manually constructed a set of systems with an increasing number of aperiodic tasks. In this way, we would have evaluated GA+CP in an arbitrarily large set of artificial subject systems, with the largest systems matching in size the most complex industrial RTES. However, this solution would have come at the cost of giving up the realistic nature of the five subject systems we presented.

Third, the experiment set-up relies on design choices that can potentially have a significant impact over the results. Specifically, we chose to run the search strategies for ten hours, and it is questionable whether a longer time could have led to significantly different results. However, by looking at the quartiles of the efficiency distributions, GA found its best results significantly earlier than ten hours. This means that in most cases, GA reached a plateau before ten hours, and the chances for it to find a better solution if given more time are likely to be low. Furthermore, GA, and consequently GA+CP, rely on parameters specific of the domain of evolutionary algorithms, i.e., the initial population size, the crossover and mutation probabilities, and the population replacement rate. Values for these parameters different from the ones we used in the experiment could have led to significantly different results. However, we used the same values used by the strategy proposed by Briand et al. [Briand et al., 2006]. These values have been derived from the GA literature and specifically tuned for deadline miss analysis. Also note that, as opposed to GA, CP is fully deterministic, hence we expect the parameter sensitivity of GA+CP to be similar to that of GA. Finally, GA+CP also depends on the neighborhood size D where CP improves the solutions found by GA (Section 7.1). Our preliminary experimentation showed that a good compromise between efficiency and effectiveness is a value of D around 1% of T. To fully mitigate this threat, we would need a systematic investigation on the impact D has on efficiency, effectiveness, diversity and scalability.

Chapter 8

Discussion and Related Work

This thesis discusses a practical approach, based on Constraint Programming (CP), to support performance stress testing in Real-Time Embedded Systems. The approach has been introduced in several peer-reviewed publications, namely in a workshop paper [Di Alesio et al., 2012], three conference papers [Nejati et al., 2012,Di Alesio et al., 2013,Di Alesio et al., 2014], and a journal paper [Di Alesio et al., 2015]. Given the scope of the thesis described in Chapter 2, we identified four relevant areas to place our work in the literature. First, we discuss related work in the field of Real-Time Embedded Systems (RTES), including scheduling theory and simulation approaches (Section 8.1). Second, we discuss related work in the field of Model-based Analysis, including UML-based methodologies for performance analysis and formal verification (Section 8.2). Third, we discuss related work in the field of software performance testing, especially in the field of Model-based Testing (MBT), and Search-Based Software Testing (SBST) Section 8.3. Finally, we discuss related work in the field of Mathematical Optimization, focusing on Constraint Programming (CP) and hybrid search strategies (Section 8.4). Note that we discuss related work in the area of Genetic Algorithms in Section 8.3, rather than Section 8.4. This is because, for topics relevant to this thesis, the work in the area of GA mostly concerns automated (stress) test case generation, which is traditionally considered along search-based methods in the field of software testing. On the other hand, the work in the area of CP relevant to this thesis is focused on scheduling analysis, which is traditionally considered along Constraint Programming applications.

8.1 Related Work in the field of Real-Time Embedded Systems

Most of the approaches for analyzing RTES are based on real-time scheduling theory (Section 2.1.1), static analysis (Section 2.1.2), and simulation (Section 2.1.3). Methods based on scheduling theory estimate the schedulability of a tasks set under a given scheduling policy [Tindell and Clark, 1994], using formulas and theorems that often assume worst case situations with respect to tasks arrival times and execution times [Baker, 2006]. However, as discussed in Section 3.1, the assumption made by theorems such as the Completion Time Theorem (CTT) and the Generalized Completion Time Theorem (GCTT) often do not hold in large and complex RTES with interdependent aperiodic tasks.

In general, results from the scheduling theory can be either too optimistic or too conservative depending on their assumptions on the task set. This might lead these theorems to overlook scenarios with deadline misses, or to predict worst-case scenarios that may never be realized in practice [David et al., 2010]. Indeed, extending these theories to realistic RTES settings with multi-core processors and interdependent, aperiodic tasks has been shown to be a challenge [Buttazzo, 2011]. This is one of the main reasons one cannot rely on scheduling theory alone when analyzing large and complex RTES. Indeed, opposite to scheduling theory, our approach does not aim at providing conditions that make a task set schedulable, but rather at generating scenarios for which performance requirements such as task deadlines, response time, and CPU usage are violated.

Note that, in general, our approach requires values for the tasks Worst-Case Execution Times (WCET). However, being targeted at the generation of worst-case scenarios, our approach can be applied both for design-time analysis and for testing when the system is implemented. In the first case, techniques for static WCET estimation can be used. On the other hand, the WCET for tasks that have been implemented can be measured by executing such tasks[1]. Also note that, in this thesis, we consider our work as a test-case generation approach, and therefore we do not discuss its advantages and drawbacks with respect to techniques specifically aimed at design-time analysis. However, we remark the commonalities our approach shares with the simulation approaches described in Section 2.1.3. Similar to Model-in-the-Loop strategies, our approach is based on a behavioral model of the system gathering the necessary data to generate stress test cases. Indeed, the generation of such test cases is the result of a search process that depends on the computational hardware of the system, e.g., the number of processor cores, and that aims at finding worst-case scenarios that depend on the external environment. The stress test cases characterize environmental triggers to the system, and can therefore be used to simulate the environment at Hardware-in-the-Loop (HiL) level.

8.2 Related Work in the field of Model-based Analysis

Other than approaches for RTES scheduling analysis based on real-time theory, there also exist model-based approaches that aim at capturing through models the real-time computation aspects of the system [Balsamo et al., 2004]. For this reason, these approaches traditionally belong to the field of Model-Driven Engineering (MDE) (Section 2.2). The idea behind these approaches is to analyze the schedulability of RTES in a system model that captures the properties of real-time tasks, such as periods, WCET, priorities, and dependencies. This provides the flexibility to incorporate specific domain assumptions and to analyze a range of possible scenarios, not just the worst-cases [Mikučionis et al., 2010]. Indeed, opposite to theorems from the real-time scheduling theory, model-based approaches can better adapt to large and complex RTES where interdependent aperiodic tasks run on multi-core processors.

In general, model-based approaches for performance and scheduling analysis are based on explicit modeling of the time and concurrency aspects of the target RTES [Di Marco and Inverardi, 2011]. Examples of such approaches include queuing networks [Lazowska et al., 1984], stochastic Petri nets [Kartson

[1] The techniques for estimating WCET have been discussed in Section 2.1.2. Since WCET are input of our approach, we do not discuss methodologies for WCET estimation as related work.

et al., 1994], and stochastic automata networks [Plateau and Atif, 1991]. Recently, there has been a growing interest in developing standardized languages to enhance the adoption of performance analysis concepts and techniques in the industry [Petriu, 2010]. The most notable these languages is the UML profile for Modeling and Analysis of Real-Time Embedded Systems (UML/MARTE or MARTE), that extends UML with modeling abstraction to support the definition of quantitative analysis methodologies for RTES (Section 2.2.2.2 and Section 2.2.2.3). Note that MARTE is a large profile that accounts for a large variety of aspects in quantitative analysis of RTES, and does not include guidelines on what abstractions to use for a particular analysis [Iqbal et al., 2012]. In this thesis, we do not provide an extension of MARTE, but rather provide guidelines on what subset of MARTE is required for stress testing. Indeed, we provide a conceptual model capturing the timing and concurrency abstractions needed for the generation of stress test cases. Then, we provide a mapping from this conceptual model to existing stereotypes in MARTE. The idea of devising a conceptual model to tailor UML profiles for a performance engineering methodology has been successfully used in the past. Examples include methodologies for deadlocks detection based on the predecessor of MARTE, the UML profile for Schedulability, Performance, and Time (UML/SPT, in short SPT) [Shousha et al., 2008], and for early scheduling analysis to design RTES in such a way that they comply to their timing constraints [Mraidha et al., 2011].

In the field of Model-Driven Software Verification, Model Checking (MC) has been successfully used to verify performance-related properties expressed in a model [Alur et al., 1990]. In MC approaches, properties typically represent conditions that should never hold in the system at any given time. These properties are formulated as reachability queries of a faulty state in a Finite-State Machine (FSM), and model checkers verify if there exists a path from the initial state of the FSM to this faulty state. MC is mostly used in software verification to compare a model with its specification, e.g., to check the absence of deadline misses in a FSM modeling task executions. In particular, real-time model checkers, e.g., UPPAAL [Behrmann et al., 2004], are commonly used for the evaluation of time-related properties. We identify three main differences between our work and MC approaches used in the context of performance analysis and testing. First, MC approaches are mostly used for *verification*, i.e., to check if a given set of real-time tasks satisfy some property of interest. Even though our approach can also be used for design-time verification, the focus of this thesis is stress testing, intended as the generation of scenarios that are likely to violate performance requirements. For this reason, our approach is complementary, and not alternative, to MC approaches. Second, software testing approaches that use MC for test case generation (Section 2.3.1) cast the performance property to be checked as a *boolean* reachability property over a FSM, in a way that a particular scenario either violates the property or does not. On the other hand, the search approaches used in this thesis for stress test cases generation are based upon the optimization of a *quantitative* objective function that expresses the extent to which a given scenario violates the performance requirement. Third, to adapt model checkers for checking different properties of real-time applications, the target system FSM has to be modeled in such a way that the target property can be formulated as a reachability query. For example, consider the problem of verifying whether the CPU usage of a system exceeds a given threshold. This problem is solved by augmenting the system FSM with an *idle* state that keeps track of the CPU time used by the tasks [Mikučionis et al., 2010]. In this way, the error states are the ones in the FSM that can be reached only when the CPU usage threshold is violated. On the other hand, the approach in this thesis is based upon the optimization of an objective function. This means that, to adapt our approach to generate test cases that stress real-time properties other than the ones we considered, one only needs to formulate a new objective function.

When it verifies that a given property does not hold in a model, MC also provides counter-examples similar to the scenarios that are the focus of our thesis. However, MC faces limitations when it comes to generating worst-case scenarios with respect to time-related properties such as task deadlines.1. Model Checking requires complex formal modeling of the system, which often leads to the well-known state explosion problem that has not been solved in the general case [Clarke et al., 2012]. 2. In practice, engineers are also interested in deadline near-misses, i.e., those scenarios where tasks are predicted to be close to missing a deadline. Indeed, since Model Checking approaches are based on estimates for the task execution times, even such scenarios have to be tested because they can lead to deadline misses during execution. 3. Model Checkers usually do not provide a usable result prior to termination. However, for practical use, testing has to be performed within a time budget. Therefore, to be effective, the generation of scenarios has to produce an usable output within the time budget, which is not the case if MC does not terminate soon enough. To the best of our knowledge, we are not aware of Model Checking approaches targeted at verifying task deadlines properties that overcome these three issues.

8.3 Related Work in the field of Software Testing

Testing multi-threaded concurrent software has traditionally focused on functional properties rather than on performance requirements [Weyuker and Vokolos, 2000]. However, the degradation in performance can have more severe consequences than incorrect system responses, and therefore testing the performance of safety-critical RTES is of paramount importance [Parnas et al., 1990].

Over the last years, there has been a growing interest in using model-based approaches (Section 2.3.1) for performance testing, which base the test case generation process on the target system and workload models [Dias Neto et al., 2007]. In particular, these approaches have been applied in the domain of distributed systems, for example concerning web applications [Shams et al., 2006], and transactional systems [Barna et al., 2011]. As it is common practice in Model-based Testing (MBT), these approaches generate abstract representation of test cases starting from the system models. These abstract test cases are then implemented in executable test cases which are run in the target system. Note that, the approach presented in this thesis also fits in this scheme, and can therefore be defined as model-based. Specifically, in our approach each abstract test case represents a sequence of arrival times for aperiodic system tasks. The abstract test cases are derived through the means of a Constrained Optimization Problem (COP) from sequence diagrams stereotyped with UML/MARTE. Note that, opposite to several MBT approaches, in this thesis we do not focus on the generation of executable test cases, nor their execution on the target system.

In industrial contexts, the problem of ensuring that system tasks satisfy their performance requirements is mostly studied by Performance Engineering techniques (Section 2.3.2), which extensively rely on profiling and benchmarking tools to dynamically analyze performance properties [Jain, 1991]. Such tools, however, are limited to producing a small number of system executions and require manual inspection of those executions. In general, these tools provide only a rough assessment of the system performance, and cannot replace systematic stress and performance testing. Recently, there has been research on automating load and stress testing through the use of PID controllers [Bayan and Cangussu, 2008]. These controllers implement feedback control loops that dynamically adjust the system inputs in order to maximize resources consumption. However, in such an approach, the controllers closely depend on the target system implementation to analyze inputs and outputs, and require a significant effort to be built. Note that this is in contrast to the principles of MBT, where only the generation of executable test cases depends on the system implementation, while abstract test cases are only tied to system models.

Search-based approaches (Section 2.3.3) have extensively been used to test non-functional system properties [Afzal et al., 2009], often in conjunction with model-based approaches. Specifically, Genetic Algorithms (GA) have successfully been used in the domain of distributed systems to support performance testing, for instance with respect to buffer overflows [Del Grosso et al., 2005], computational resources consumption [Berndt and Watkins, 2005], Quality of Service (QoS) constraints [Shams et al., 2006], and network traffic [Garousi et al., 2008]. However, these approaches do not tackle hard real-time constraints such as deadline misses, as these properties are mostly important in RTES. In this domain, GA have also been used to generate test cases for testing timeliness properties, showing that it is able to run in large systems where the execution of MC approaches failed [Nilsson et al., 2006]. However, the main contribution of Nilsson et al. is a mutation-based testing criterion to assess test adequacy, which is beyond the scope of this thesis. Therefore, as for testing hard real-time properties such as deadline misses, the state-of-the-art is represented by the work of Briand et al. [Briand et al., 2006]. In this thesis, we first use that work as a comparison baseline for Constraint Programming (CP), and then as the GA part of our combined GA+CP approach.

8.4 Related Work in the field of Mathematical Optimization

Approaches based on Constraint Programming (CP) have been applied for a long in the field of scheduling analysis [Baptiste et al., 2001], especially concerning job-shop scheduling problems in the manufacturing domain [Le Pape and Baptiste, 1997]. Among those, several approaches target task real-time constraints such as task deadlines [Hladik et al., 2008], or timeliness [Malapert et al., 2012]. Preemptive scheduling problems have also been solved both with pure CP [Cambazard et al., 2004], and with hybrid approaches featuring combinations with GA [Yun and Gen, 2002]. Furthermore, recent implementations [Laborie, 2009] have successfully used IBM ILOG CP OPTIMIZER and OPL for scheduling problems, albeit not addressing task preemption. However, the goal of schedulability analysis approaches is to assess whether or not the system tasks are schedulable, i.e., to find scenarios where tasks do not miss their deadlines. In this thesis, we have the opposite goal, as we are interested in generating scenarios that violate performance requirements, i.e., to find scenarios that break task deadlines and thresholds on response time and CPU usage. In the context of stress testing, CP has been used to generate stress test cases for multimedia systems [Zhang and Cheung, 2002]. The main focus of that work is to investigate memory saturation at runtime under heavy loads, as opposed to task deadlines, response time and CPU usage.

Despite the extensive literature for constraint based scheduling, we are unaware of CP approaches targeted to test case generation, such as the generation of worst case scenarios, and of approaches that consider all of the specific complexities of RETS such as multi-core architectures, task dependencies, aperiodic tasks, and preemptive scheduling policies. Nonetheless, these approaches have greatly inspired us to consider CP in this thesis.

Note that, for the purpose of generating worst-case scenarios for stress testing, CP differs with GA approach in three main respects. (1) The formulation of Constrained Optimization Problems (COP) in CP enables the use of complete search methods, such as branch and bound (Section 2.4.1). On the other hand, metaheuristics such as GA are randomized and incomplete approaches that explore only part of the search space. This means that, upon termination, CP returns the global optimal solution, while GA can not guarantee that the best solution found is a global optimum. (2) Unlike GA, CP is deterministic and does not rely on a set of parameters that have a significant impact on the search and therefore need to be tuned, such as GA crossover and mutation probabilities, population size and replacement strategy. (3) In CP, the choice of the solver used to solve the COP depends on the shape of the objective function of the problem. For instance, one cannot use non-integer objective functions with finite-domain solvers, while GA this does not have this limitation.

There also have been various contributions in the area of hybrid search strategies to solve hard combinatorial problems [Raidl, 2006], especially in the direction of combining CP with probabilistic meta-heuristics [Focacci et al., 2003]. For instance, GA has been successfully used in the past to solve COP [Homaifar et al., 1994]. There has also been interest in devising techniques to combine CP and local search [Hentenryck and Michel, 2009]. Most of these approaches compute a set of initial solutions at random, and then optimize them by exploring their neighborhood [Mladenović and Hansen, 1997]. For instance, Large Neighborhood Search [Shaw, 1998] systematically explores subpart of the search space by relaxing current sub-optimal solutions and using constraint propagation to find better solutions. Despite this large number of hybrid search strategies, we are unaware of applications that are targeted at testing timing properties by generating stress test cases. However, the search strategy presented in our work shares several commonalities with existing work. Specifically, we use CP to completely explore a neighborhood of a solution computed externally, similar to Pesant et al. when they solved the Traveling Salesman Problem [Pesant and Gendreau, 1996]. As opposed to Guimarans et. al [Guimarans et al., 2011] that used the Clark and Wright Savings Heuristic to generate an initial set of solutions to further optimize with CP, we use a state-of-the-art GA solution [Briand et al., 2006] instead.

We finally point out how, in contrast to strategies where GA is used as a mean to explore the CP search tree [Iwamura and Liu, 1996], GA and CP are independent in our approach, as the latter is used only once the solutions have been computed by the former. The general idea of combining search-based approaches and constraint programming has already proven successful in the field of automated test data generation. For instance, Lakhotia et al. devised an approach aimed at test data generation in the presence of pointer inputs and dynamic data structure. The approach combines a CP-based lazy initialization technique adapted from symbolic execution with search-based testing [Lakhotia et al., 2010]. Other approaches combine global and local search, in such a way that solutions are initially computed by global search, and subsequently refined through local search. These approaches are commonly known under the name of Memetic Algorithms [Moscato et al., 2004], and are based upon the same behavior of GA+CP, i.e., finding initial solutions, and then improving them. Memetic algorithms have successfully been applied in the domain of Search-based Software Testing for the generation of test data [Harman and McMinn, 2010] and test suites [Fraser et al., 2014].

Chapter 9

Conclusions and Future Work

Real-Time Embedded Systems (RTES) in safety critical domains have to react to external events within strict timing constraints. Failure to do so poses great risks for the system safety, as even a single task missing its deadline could result in a failure with severe consequences for the system itself, its users, and the environment. For this reason, systematic performance evaluation is of paramount importance to assess the system capability to operate safely. In the context of safety-critical RTES, the three main performance-related aspects which have to be thoroughly investigated concern hard real-time, soft real-time, and resource usage constraints. However, the system environment plays a major role in determining the inputs, and as a result their timing can never be fully predicted prior to the system execution. For assessing whether or not the expected performance is met at runtime, several techniques have been proposed, ranging from design verification to testing. In particular, stress testing approaches have been developed with the goal of identifying scenarios that are likely to violate performance requirements. Due to the large domain of system inputs, stress testing has often been cast as a search problem over the space of task arrival times. The best known search-based approach that has been used for generating stress test cases is based on metaheuristic search, namely Genetic Algorithms (GA).

For practical use, it is essential to investigate the trade-off between the time a stress testing approach needs to generate stress test cases (efficiency), their capability to reveal scenarios that violate performance requirements (effectiveness), and to cover different scenarios where such violations arise (diversity). This trade-off is mostly determined by the search strategy used for generating stress test cases. Even though GA has proven to be efficient and capable of finding solutions highly diverse from each other in a variety of problems, GA is an incomplete and randomized search strategy that explores only part of the input space. This means that a suboptimal choice for the initial population and the search parameters could drive the search to subspaces with ineffective solutions. This reason justifies the investigation of alternatives to GA, such as complete search strategies based on Constraint Programming (CP), for identifying worst-case scenarios with respect to performance requirements.

Furthermore, when devising a stress testing approach suitable for industrial use, choosing the appropriate search strategy is not the only concern. Indeed, since RTES require domain-specific configurations, a conceptual model capturing specific system and contextual properties is required to enable effective stress testing. However, the conceptual model itself is not sufficient because, to enable effective industrial use, stress testing has to be capable of seamless integration in Model-Driven Engineering (MDE) development processes. Therefore, the conceptual model has to be mapped to a standard modeling language, such as the Unified Modeling Language (UML). In the context of RTES, reasoning about performance requirements such as deadline misses, response time, and CPU usage requires the explicit modeling of time, which is one of the key characteristics of the UML Profile for Modeling and Analysis of Real-Time and Embedded Systems (UML/MARTE, in short MARTE). Therefore, MARTE represents the reference modeling framework when mapping the abstractions needed for stress testing to a standard modeling language.

In this thesis, we introduce three main contributions aimed at supporting the generation of stress test cases in RTES (Section 9.1). Specifically, the contributions include (1) a conceptual model, mapped to UML/MARTE, which captures the abstractions required to generate stress test cases (Section 9.1.1), (2) a constraint optimization model to generate such test cases (Section 9.1.2), and (3) a combined GA+CP search strategy for stress testing that achieves a practical trade-off between efficiency, effectiveness and diversity (Section 9.1.3). The validation of our work shows that the conceptual model can be applied with a reasonable overhead in an industrial settings, that CP is able to effectively identify worst-case scenarios with respect to task deadlines, response time, and CPU usage, and that the combined GA+CP strategy is more likely than GA and CP in isolation to scale to large and complex systems. Experimental results leave room for improvement, for example considering further combinations of meta-heuristic and complete search, and test suite reduction techniques to find the minimal set of solutions yielding a given level of effectiveness and diversity. In addition to improvements to the proposed approach, this thesis opens up the exploration of further directions in the area of software testing and analysis (Section 9.2). Such directions involve (1) the investigation of multi-objective optimization to generate stress test cases that simultaneously exercise different performance properties of the system, and (2) the derivation of design guidelines to configure software parameters in a way to minimize the risk performance requirements are violated at runtime.

9.1 Summary of the Contributions

To address the challenges described above, this thesis proposes a practical approach based on Constraint Programming (CP) to support performance stress testing in Real-Time Embedded Systems (RTES). Our approach expresses the generation of stress test cases as a search problem over the space of task arrival times. In this way, each solution to the problem, i.e., each sequence of arrival times for aperiodic task executions, characterizes one test case. The worst-case analysis performed by our approach is based on a description of the system, and its executing platform. In particular, the input for the approach is derived from UML models, e.g., sequence diagrams, stereotyped with MARTE. This allows our methodology to be seamlessly integrated in MDE-compliant development processes.

9.1.1 A conceptual model to support stress testing in Real-Time Systems

In Chapter 5 we define a conceptual model that captures, independently from any modeling language, the abstractions required to support stress testing of task deadlines, response time, and CPU usage in RTES. We also provide a mapping between our conceptual model and UML/MARTE, in order to simplify its application in standard MDE tools. The subset of UML/MARTE that corresponds to out conceptual model contains tagged values and stereotypes that extend UML sequence diagrams, which are popular for modeling concurrent systems such as RTES.

The conceptual model has been validated in a Fire and Gas monitoring System (FMS) from the maritime and energy domain concerning performance requirements for safety-critical I/O drivers. The validation showed that the conceptual model can be applied in industrial settings with a reasonable overhead, and enables the definition of a search strategy for worst-case scenarios with respect to performance requirements. This contribution has been published in a conference paper [Nejati et al., 2012].

9.1.2 A CP-based strategy to identify worst-case scenarios in RTES

In Chapter 6 we cast the problem of generating stress test cases for task deadlines, response time, and CPU usage as a Constraint Optimization Problem (COP) over our conceptual model. The COP implements a preemptive task scheduler with fixed priorities and, upon resolution, generates worst-case scenarios that can be used to characterize stress test cases. This CP-based strategy is proposed as an alternative to the state-of-the-art relying on metaheuristic search, such as Genetic Algorithms (GA). CP offers a number of potential advantages over GA, which makes its investigation worthwhile in our context: it can potentially guarantee the completeness of the search provided it has sufficient time, and, being deterministic, it does not need its users to take into account parameters such as mutation and crossover probabilities, population size and replacement rate. The key idea behind the formulation of the identification of worst-case scenarios with respect to performance requirements relies on five main points. (1) modeling the system design, which is static and known prior to the analysis, as a set of constants, while (2) modeling the system properties that depend on runtime behavior as a set of variables. (3) In this way, the Real-Time Operating System (RTOS) scheduler is modeled as a set of constraints among such constants and variables, and (4) the performance requirement to be tested, i.e., task deadlines, response time, or CPU usage, is an objective function to be maximized. (5) Finally, the logic behind the RTOS scheduler can be encapsulated in an effective labeling strategy over the variables of the model, so that the search is more likely to quickly converge to optimal solutions.

The validation of the COP in the FMS showed that CP is effectively able to find scenarios that break task deadlines and violate response time and CPU Usage requirements. On the other hand, a second validation on five subject systems from safety-critical domains showed that, when compared to GA, CP is more effective, but less efficient and generates stress test cases that are less diverse. This result raises the need for exploring further search strategies in order to achieve an optimal trade-off between efficiency, effectiveness, and diversity. This contribution is the result of a refinement process over four iterations in two years, which have been published as a workshop paper [Di Alesio et al., 2012], and three conference papers [Nejati et al., 2012, Di Alesio et al., 2013, Di Alesio et al., 2014].

9.1.3 A GA+CP search strategy to identify worst-case scenarios in RTES

In Chapter 7 we described a search strategy to generate stress test cases, namely GA+CP, that combines GA and CP to provide higher scalability by retaining the efficiency and solution diversity of GA, and the effectiveness of CP. The key idea behind GA+CP is to improve the solutions computed by GA by performing a complete search with CP in their neighborhood. Specifically, our approach consists of two separate stages. First, the search problem is solved through GA, using a state-of-the-art implementation for generating scenarios that are likely to reveal task deadline misses. This step produces an initial set of solutions, each characterizing a stress test case. Second, for each solution found by GA, CP searches in its neighborhood for better solutions through the constraint optimization model we defined. This step produces the final set of solutions. In this way, GA+CP takes advantage of the efficiency of GA, because solutions are initially computed with GA, and the subsequent CP search is likely to terminate in a short time since it focuses on the neighborhood of a solution, rather than on the entire search space. GA+CP also takes advantage of the diversity of the solutions found by GA, because CP performs a local search in subspaces defined by GA solutions. Similarly, GA+CP takes advantage of the effectiveness of CP since, once GA has found a solution, CP further improves it by either finding the best solution within the neighborhood, or proving upon termination that no better solution exists.

GA+CP has been validated with the same five subject systems used to evaluate the CP-based strategy. This validation showed that, in comparison with GA and CP in isolation, GA+CP achieves nearly the same effectiveness as CP and the same efficiency and solution diversity as GA, thus combining the advantages of the two techniques. Even though the scalability of GA+CP needs to be further ascertained, this result is encouraging, and is a significant step forward from GA and CP in isolation, towards a stress testing approach suitable for industrial-size problems. This contribution has been accepted for publication in a journal [Di Alesio et al., 2015].

9.2 Perspectives and Future Work

The validation of GA+CP has been conducted on a set of five subject systems varying in size and complexity. However, there might be larger systems than those considered, and for which the efficiency, effectiveness, and diversity of GA+CP needs to be investigated. A systematic scalability analysis of GA+CP entails the generation of a set of artificial systems with increasing number ot tasks and dependencies. Such systematic scalability analysis might pose new challenges for the improvement of our stress testing search strategy, possibly leading to the definition of further ways to combine complete and meta-heuristic search. Furthermore, a more detailed industrial application of our strategy might uncover the need of optimizing the set of solutions identified by our approach. For example, in cases where a large set of solutions is identified, test suite reduction techniques can be used to find the minimal set of solutions yielding a desired level of effectiveness and diversity.

In addition to improvements to the proposed approach, this thesis opens up the exploration of two further directions in the area of software testing and analysis, concerning the identification of scenarios which are predicted to violate more than one performance requirements (Section 9.2.1), and the derivation of guidelines to configure tunable parameters at design time, so that the system is as likely as possible to meet its expected performance (Section 9.2.2).

9.2.1 Identifying Worst-case Scenarios with respect to Several Requirements

In this thesis, we focus on the problem of identifying worst-case scenarios with respect to a single performance requirement, namely task deadlines, response time, and CPU usage. This is because, in safety critical systems, a scenario that violates even a single performance requirement poses a severe threat to the system safety. However, some real-time applications might tolerate some cases where performance requirements are violated. This is common in soft real-time systems, which, provided that enough computational resources are available, are able to recover from short deadline misses. For these systems, we could consider multi-objective optimization in order to generate test cases that push tasks to miss their deadlines while at the same time leading to high CPU usage. Such test cases would be able to uncover scenarios where deadline misses are more severe, because they happen when the system has not enough free CPU time to recover in a timely manner. Indeed, a Pareto analysis considering more than one fitness/objective function at a time could identify as stressful scenarios where no performance requirement is explicitly violated. For instance, there might be systems where particular high values of CPU usage and response time pose safety risks, even if they both remain under their specified thresholds.

9.2.2 Deriving Design Guidelines for Parameters Configuration

In general, full exploitation of the benefits of systematic software engineering methodologies requires, in the context of safety-critical RTES, a flexible approach that focuses on system performance both during design and testing. Such strategy has to support developers in (1) designing the system in a way that performance requirements are as likely as possible to be satisfied during operation, and (2) exercising the system in a way that performance requirements are as likely as possible to be violated during testing. While (2), covered by this thesis, aims at providing satisfactory evidence that the system performance has been thoroughly tested, (1) complementarily ensures that performance is engineered at early development stages, in order to mitigate the impact of late architectural changes. We envision that such flexibility can be achieved with the current design of the approach we proposed, due to the fact that the worst-case scenario analysis is cast as an optimization problem.

In particular, the focus of this thesis is stress testing, which is an important activity to carry out in order to mitigate the risks in safety-critical systems. In stress testing, the goal is to derive worst-case scenarios with respect to performance requirements, that characterize stress test cases representing the worst operational conditions in terms of arrival times for aperiodic tasks. However, in the way our approach is designed, it is possible to instead identify scenarios in terms of tunable parameters of the system, such as delay or offset times for periodic tasks. Particular scenarios minimizing the impact of requirements violations in the worst case could then be used to characterize design guidelines for optimal performance, in order to build systems that are as likely as possible to meet their expected performance.

To perform this kind of analysis, we would need to consider a search strategy that differs from the one we defined in two aspects. First, the search would consider, in addition to variables modeling the environment, a set of parameters that can be tuned at design time. Examples of such parameters include, among others, task priorities and periods. Second, instead of maximizing an objective/fitness function modeling a performance requirement, the search would perform a *MiniMax* analysis with the goal of identifying values for the tunable parameters that lead to worst-case scenarios that are as close as possible to satisfy, rather than to violate, performance requirements.

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