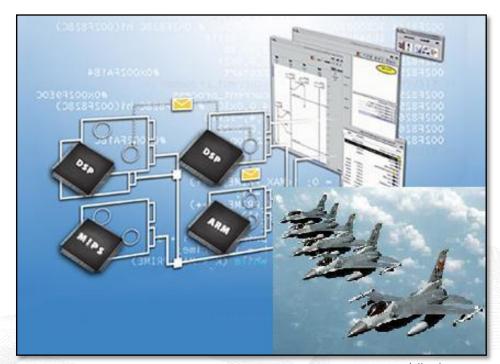
Testing Deadline Misses for Real-Time Systems Using Constraint Optimization Techniques

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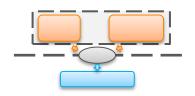


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We present a technique to use Constraint Optimization to test deadline misses for RTES



Performance Requirements (PRs) vs. Real Time Embedded Systems (RTES)



Using Constraint Programming for Verification and Validation of RTES

	j _o	j_1	j ₂
exec(j)	2	2	2
p(j)	100	101	102
dl(j)	3	2	3
max_ia(j	3	2	3
min_dr(j max_dr(j	3	2	3

Evaluation, Experience and Current Work

RTES are typically safety-critical, and thus bound to meet strict Performance Requirements



control-link.net

Performance Requirements are the most difficult requirements to verify



They depend on the environment the software interacts with (hw devices)

libelium.com



They depend on the computing platform on which the software runs



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They constraint the entire system's behavior and thus can't be checked locally

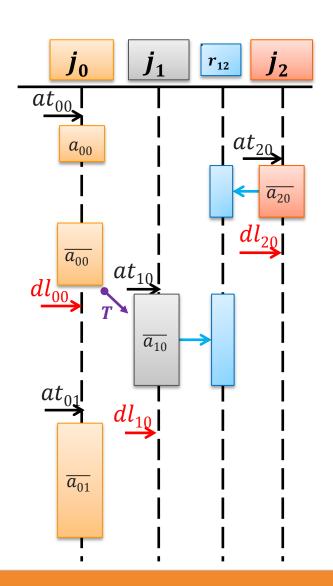
tasks which have to finish before their deadlines



Each task has a deadline (i.e., latest finishing time) w.r.t. its arrival time

Some task properties depend on the environment, some are design choices

Each task can trigger other tasks, and can share computational resources with other tasks

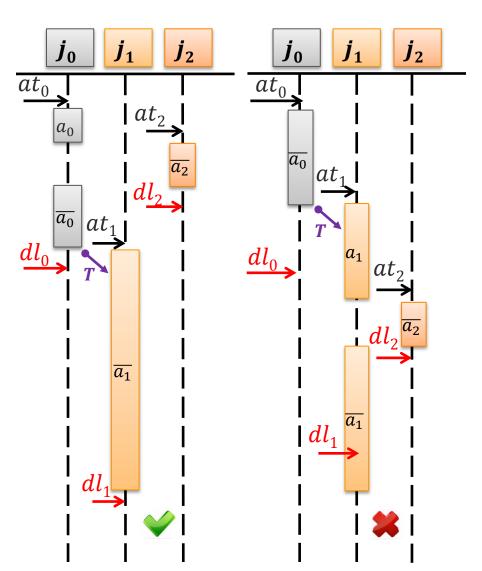


Particular sequences of arrival times of tasks can determine deadline miss scenarios



 j_0, j_1, j_2 arrive at at_0, at_1, at_2 and must finish before dl_0, dl_1, dl_2

 j_1 can miss its deadline dl_1 depending on when at_2 occurs!



We are looking for sequences of arrival times maximizing the likelihood of deadline misses



Arrival times for tasks in a RTES depend on the environment

 $a_1 = 1$ $a_2 = 3$ $a_3 = 3$ $a_4 = 7$

Arrival times can be tuned during software testing

$$a_1 = 1$$
 $a_2 = 3$
 $a_3 = 4$
 $a_4 = 7$

Real Time Embedded System

Real Time Embedded System





A sequence of arrival times identified by our approach as likely to lead to a deadline miss defines a Stress Test Case

This problem has been well studied, but each existing approach has its weaknesses



	Schedulability	Model	Genetic
	Theory	Checking	Algorithms
Basis	Mathematical	System	System
	Theory	Modeling	Modeling
Background	WCET, Queuing Theory, etc.	Fixed-point Computation	Meta-Heuristic Search
Key Features	Theorems [1]	Graph-based / Symbolic [2]	Non-Complete Search [3]
Weaknesses	Assumptions,	Complex	Non-Exhaustive
	Multi-Core	Modeling	Search

^[1] J. W. S. Liu, "Real-Time Systems". Prentice Hall, 2000

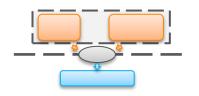
^[2] M. Mikucionis, K. Larsen, B. Nielsen, J. Illum, A. Skou, S.Palm, J.Pedersen, and P. Hougaaard, "Schedulability analysis using UPPAAL: Herschel-Planck case study", in ISoLA, 2010

^[3] L. Briand, Y. Labiche, and M. Shousha, "Using genetic algorithms for early schedulability analysis and stress testing in real-time systems", Genetic Programming and Evolvable Machines, vol. 7 no. 2, pp. 145-170, 2006

We model the RTES Design, Platform and PRs through a Integer Linear Program solved by CPLEX

The System is modeled through **Performance Requirements are** constants, variables and constraints modeled as objective functions **RTES** System Design Performance & Platform Requirements input Optimization Engine output Stress Test Cases **Stress Test Cases are the optimal** solutions for the constraint program

Our approach tries to mitigate some weaknesses found in related works



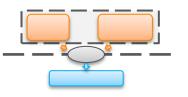
	Schedulability Theory	Model Checking	Genetic Algorithms	Our Approach
Basis	Mathematical Theory	System Modeling	System Modeling	System Modeling
Background	WCET, Queuing Theory, etc.	Fixed-point Computation	Meta-Heuristic Search	Mathematical Optimization
Key Features	Theorems [1]	Graph-based / Symbolic [2]	Non-Complete Search [3]	Complete Search
Weaknesses	Assumptions, Multi-Core	Complex Modeling	Non-Exhaustive Search	Performance / Scalability (?)

^[1] J. W. S. Liu, "Real-Time Systems". Prentice Hall, 2000

^[2] M. Mikucionis, K. Larsen, B. Nielsen, J. Illum, A. Skou, S.Palm, J.Pedersen, and P. Hougaaard, "Schedulability analysis using UPPAAL: Herschel-Planck case study", in ISoLA, 2010

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Tasks and Platform design properties are modeled through constants

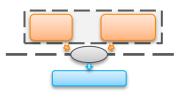


Assumption 1: The scheduler checks tasks for preemptions at regular intervals (tq)

Assumption 2: The context switching time between tasks is negligible w.r.t. *tq*

```
// T: Observation interval (range of
time quanta)
int tq = \dots;
range T = 0..tq-1;
// c: Number of Processor Cores
int c = \ldots;
// n: Number of tasks
int n = \ldots;
range J = 0..n-1;
tuple TaskExecution {
int task;
int execution;
int priority[J] = \dots;
int task deadline[J] = ...;
int max interarrival time[J] = ...;
int min duration[J] = ...;
int max duration[J] = ...;
int triggers [J, J] = ...;
int dependent [J, J] = ...;
```

Tasks and Platform real time properties are modeled through variables



Timo quanta

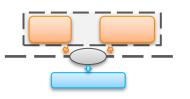
 $efe(a) \stackrel{\text{def}}{=}$ earliest time when a could start if an unlimited number of cores was available

 $active(a, t) \stackrel{\text{def}}{=} \begin{cases} 1 & \text{if } a \text{ is executing at time } t \\ 0 & \text{otherwise [1]} \end{cases}$

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Su		0	1	2	3	4	5	6	7
utio	a_0	1	0	0	0	0	0	1	0
executions	a_1	0	0	0	0	0	0	0	1
ke	a_2	0	1	1	0	0	1	0	0
Task (a_3	0	0	0	1	1	0	0	0

[1] C.L. Pape and P. Baptiste, "Resource Constraints for preemptive job-shop Scheduling", Constraints, vol. 3, no. 4, pp. 263-287, 2098

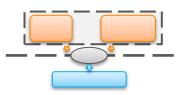
The Platform Scheduler behavior is modeled through 5 sets of constraints



1. Well-Formedness: relations directly following from variables definitions

```
/* I. Well-formedness constraints */
forall(a in A) {
     wf3: eligible for execution[a] <=</pre>
               start[a];
     wf4: start[a] <= end[a];</pre>
     if(prevc(A, a).task == a.task)
          wf6: eligible for execution[a] ==
                     maxl(arrival time[a],
                          end[prevc(A, a)]);
     else
          wf7: eligible for execution[a] ==
                     arrival time[a];
     wf8: duration[a] == sum(t in T)
               active[a, t];
     forall(t in T) {
          wf9: t == start[a] \Rightarrow active[a, t]
               == 1:
          wf10: t == end[a] - 1 => active[a,
               tl == 1;
          wf11: t \le start[a] - 1 =>
                      active[a, t] == 0;
          wf12: t \ge end[a] = active[a, t]
                     == 0:
```

The Platform Scheduler behavior is modeled through 5 sets of constraints

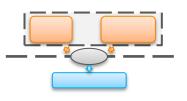


2. Temporal Ordering: executions, triggering and resource usage relations

3. Multicore: computing capacity of the platform

```
/* III. Multi-core Constraint */
forall(t in T)
   mc: sum(a in A) active[a, t] <= c;</pre>
```

The Platform Scheduler behavior is modeled through 5 sets of constraints

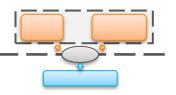


4. Preemptive Scheduling: priority-driven preemptive scheduling behavior

```
/* IV. Preemptive Scheduling Constraints */
forall(t in T, a0 in A, a1 in A)
   ps2: (active[a0, t] == 0 &&
        active[a1, t] == 1 &&
        sum(a2 in A) active[a2, t] == c &&
        eligible_for_execution[a0] <= t &&
        end[a0] >= t+1)
        =>
        (priority[a1.task] >=
        priority[a0.task]);
```

```
5. Good CPU Usage: scheduler's CPU Usage optimizations
```

The Performance Requirement is modeled as an objective function to maximize



The objective function is a counter for deadline misses

Main limitation: each deadline miss is given the same weight in the sum

$$f \stackrel{\text{def}}{=} \sum_{i} max(0, min(1, e(a_i) - dl(a_i)))$$

Potential alternative [1]: non-linear objective function to weight deadlines

$$\tilde{f} \stackrel{\text{def}}{=} \sum_{i} 2^{e(a_i) - dl(a_i)}$$

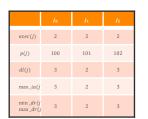
[1] L. Briand, Y. Labiche, and M. Shousha, "Using genetic algorithms for early schedulability analysis and stress testing in real-time systems", Genetic Programming and Evolvable Machines, vol. 7 no. 2, pp. 145-170, 2006

Correctness was evaluated analyzing the results computed starting from a set of toy examples

	j_0	j_1	j_2
exec(j)	2	2	2
p(j)	100	101	102
dl(j)	3	2	3
$\max_i a(j)$	3	2	3
$\min_{d} r(j)$ $\max_{d} r(j)$	3	2	3

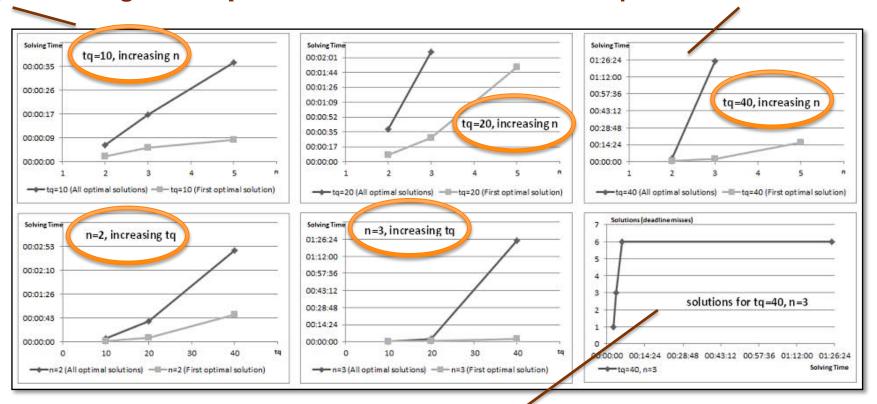
In this case, we found a solution where both executions of task j_0 miss their deadline

Performance was evaluated by measuring solving times with increasing input size



We evaluated Performance by increasing n and tq

It took a significant amount of time to find all optimal solutions



Most optimal solutions were found shortly after the search started, even if the search took a much more time to terminate

Our current work relies on improving the approach scalability with respect to n and tq

	j _o	j_1	j_2
exec(j)	2	2	2
p(j)	100	101	102
dl(j)	3	2	3
max_ia(j	3	2	3
min_dr(j max_dr(j	3	2	3

	0	1	2	3	4	5	6	7
a_0	1	0	0	0	0	0	1	0
a_1	0	1	1	1	0	1	0	0
a_2	0	0	0	0	1	0	0	0

Problem: it's hard to compute the *active* matrix $(2^{n*exec(j_n)*tq}$ possible values)

	0	1	2	3	4	5	6	7
a_0	1						1	
a_1		1	1	1		1		
a_2					1			

	running in
a_0	[0,1), [6,7)
a_1	[1,4), [5,6)
a_2	[4,5)

Idea: we don't really need the whole matrix, but just to know where the 1's are!

In summary, Constraint Optimization is a promising approach to derive Stress Test Cases for RTES

System Platform, Tasks and PRs are modeled in a Constraint **Program**

Solving the CP finds tunable values more likely to stress test the system

Significant advantages over other approaches encourage future work



Questions?