

UNIVERSITY OF TWENTE.

Formal Methods & Tools.

State Space Reduction of Linear Processes using Control Flow Reconstruction

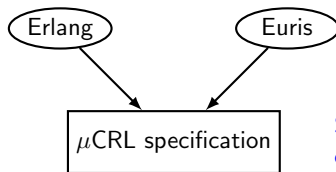
Mark Timmer

October 14, 2009

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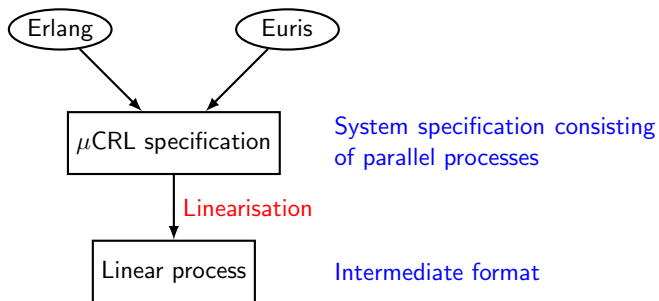
- 1 Introduction
- 2 Reconstructing Control Flow Graphs
- 3 Data Flow Analysis
- 4 Transformations
- 5 Case studies
- 6 Conclusions and Future Work

The μ CRL toolset

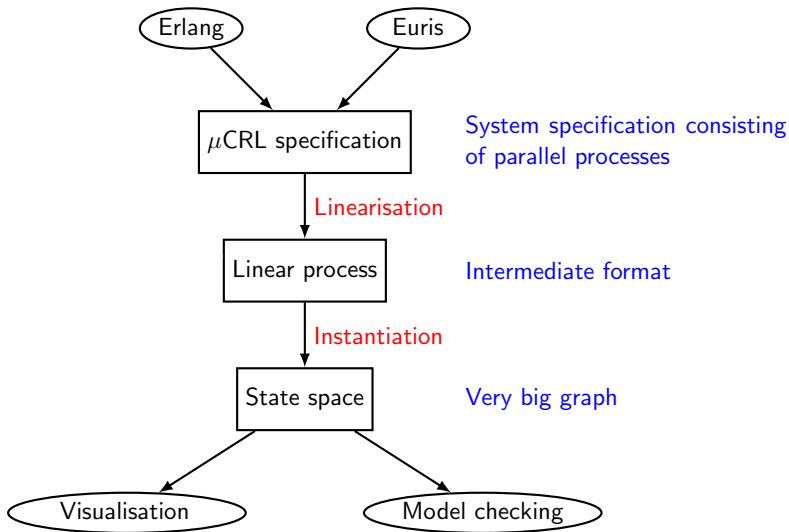


System specification consisting of parallel processes

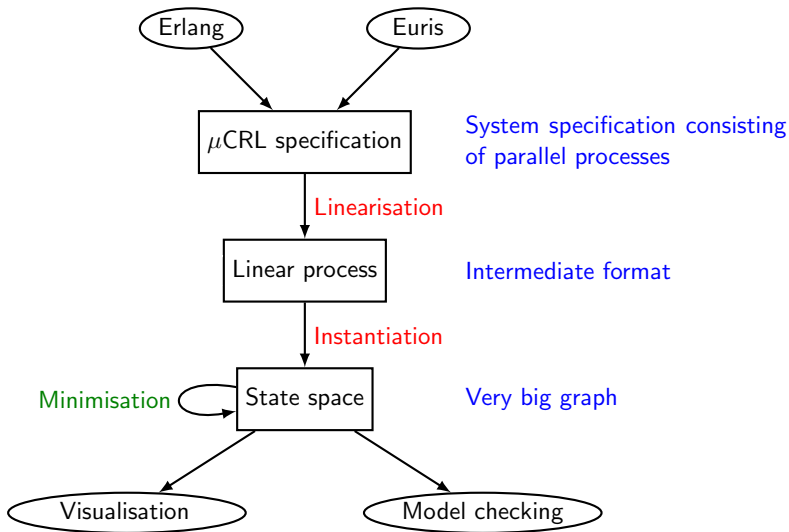
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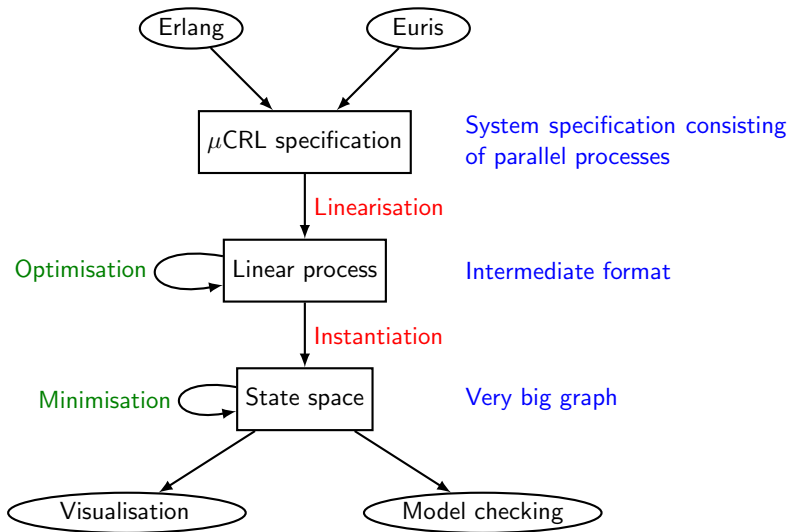
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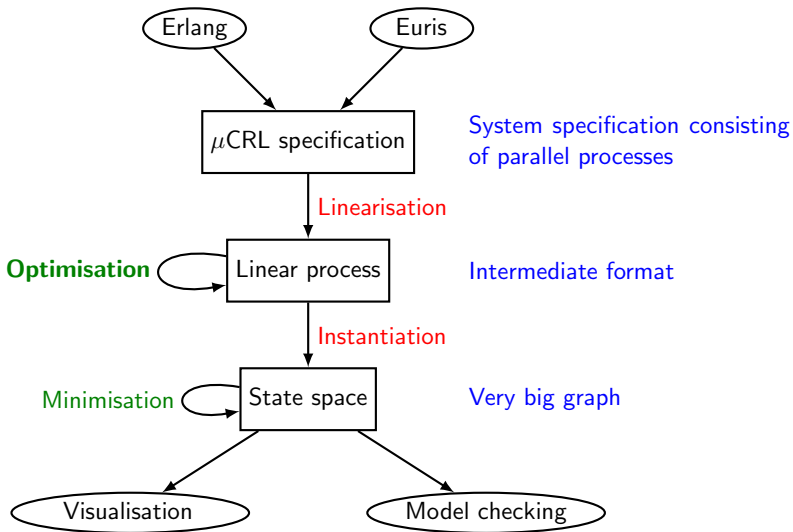
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The linear process equation

The basic structure of an LPE

$$\begin{aligned} X(d : D) = & \sum_{e_1 : E_1} c_1(d, e_1) \Rightarrow a_1(d, e_1) \cdot X(g_1(d, e_1)) \\ & + \dots \\ & + \sum_{e_n : E_n} c_n(d, e_n) \Rightarrow a_n(d, e_n) \cdot X(g_n(d, e_n)) \end{aligned}$$

- d : a vector of global **state variables**
- e_j : a vector of **local variables** for summand i
- c_j : the **enabling condition** for summand i
- a_j : the (parameterised) **action** for summand i (possibly τ)
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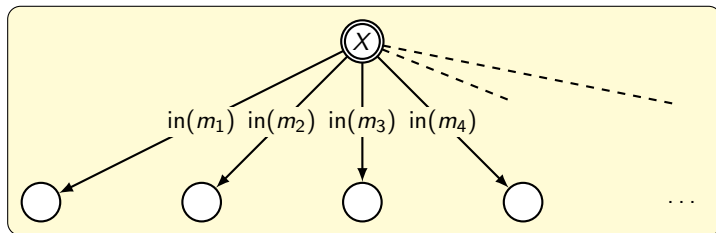
$$d \xrightarrow{a(p)} d' \Leftrightarrow \exists i . \exists e_i . c_i(d, e_i) = \text{true} \wedge a_i(d, e_i) = a(p) \wedge g_i(d, e_i) = d'$$

An example

$$X = \sum_{m:\{m_1,\dots,m_{10}\}} \text{in}(m) \cdot (\tau \cdot \text{loss} \cdot X + \tau \cdot \text{out}(m) \cdot X)$$

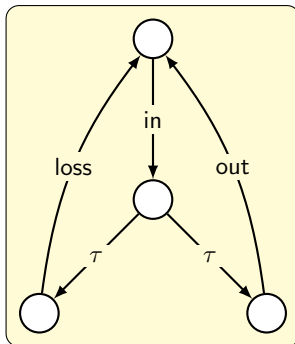
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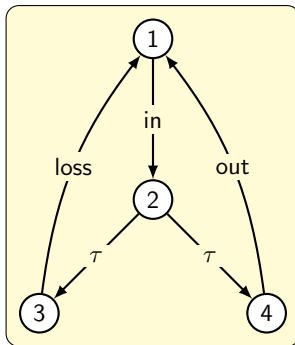
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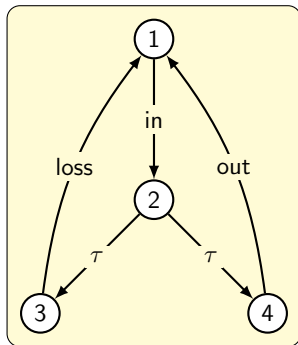
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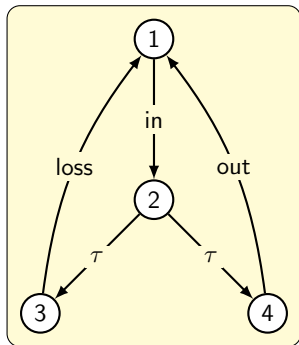
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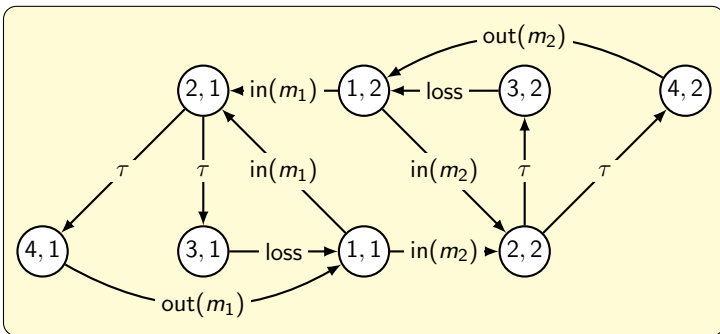
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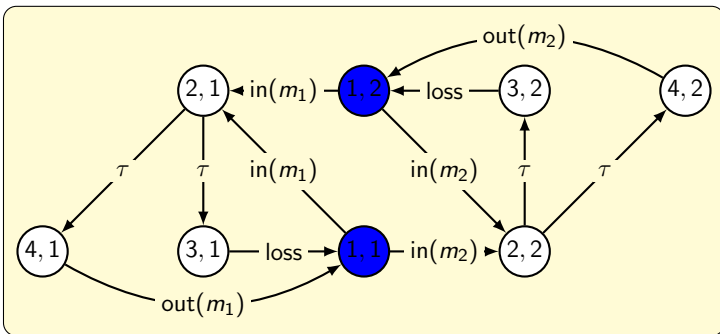
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Initial process: $X(1, m_1)$.

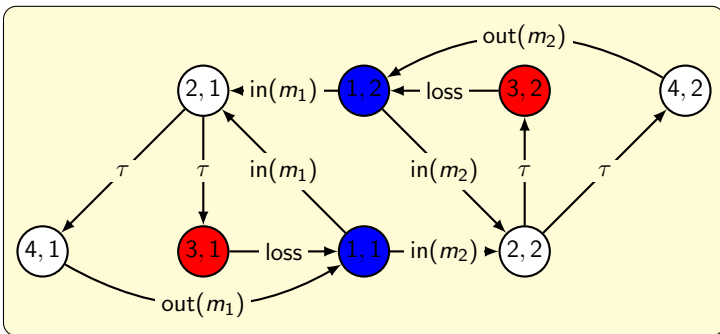
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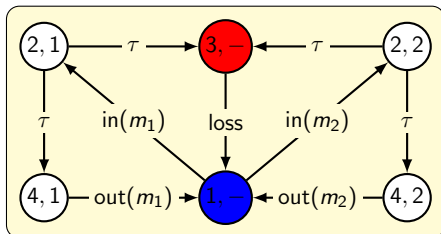
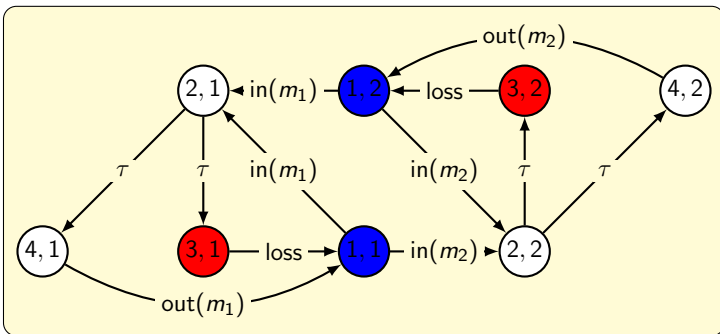
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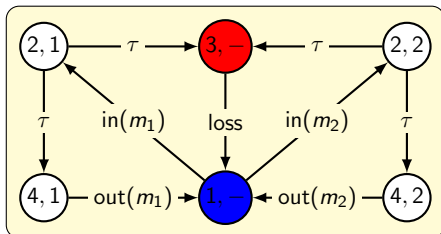
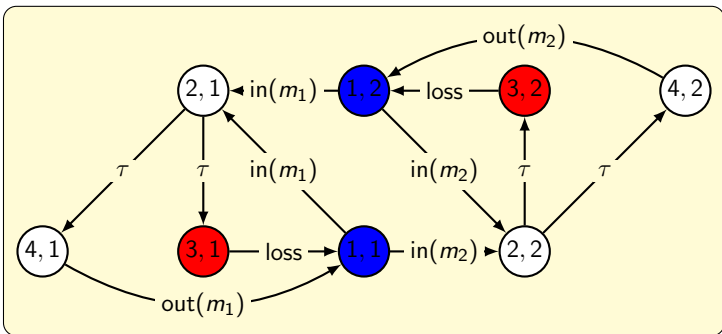
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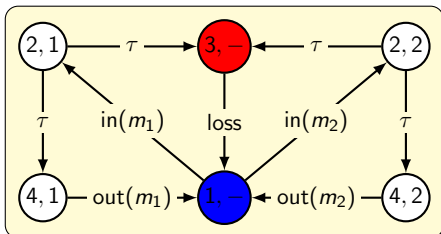
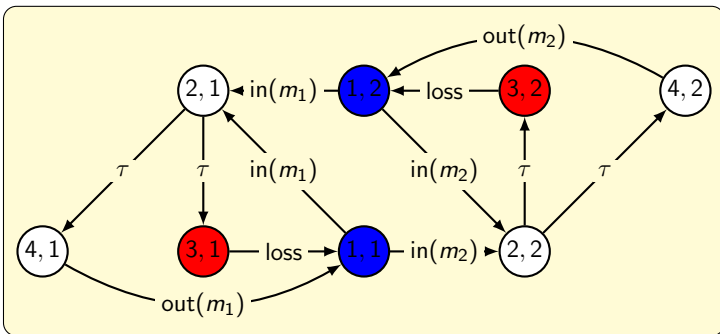


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Solution:

- 1 Detect **control flow parameters**
- 2 Identify **clusters** of summands
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- 4 Deduce when data parameters are (globally) **relevant**
- 5 **Transform** the LPE

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Observation: program counters ([control flow parameters](#)) are special.

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$$B_1 = \sum_{d: D} \text{read}(d) \cdot w(d) \cdot B_1$$

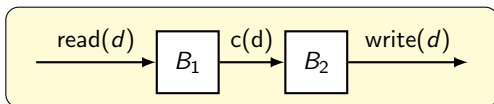
$$B_2 = \sum_{d: D} r(d) \cdot \text{write}(d) \cdot B_2$$

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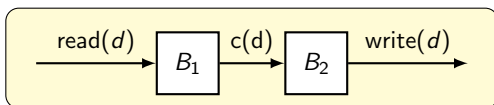


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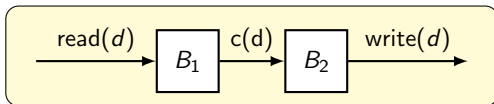
$$X(a: \{1, 2\}, b: \{1, 2\}, x: D, y: D) =$$

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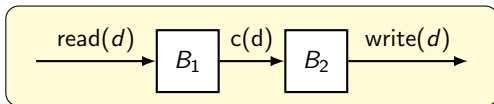


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In every summand, each control flow parameter

- is either left **unchanged**, or
- has a clear **transition** from a **source** value to a **destination** value

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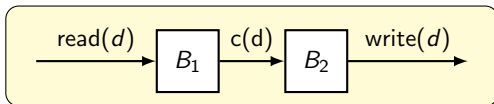


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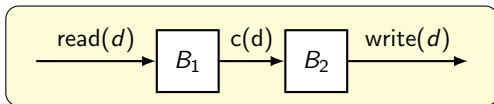


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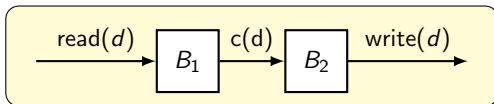


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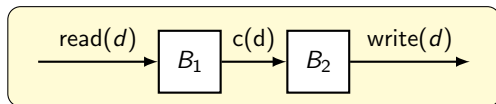


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Control Flow Graph

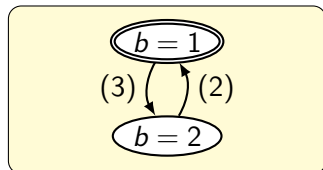
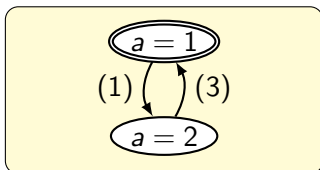


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The *belongs to* relation

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A data parameter k **belongs to** a CFP j if the **cluster** of j contains all summands that

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So, x **belongs to** a and y **belongs to** b . Thus, **relevance** of x can be decided by looking only at the **control flow** of a .

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So: $R(y, b, 2)$ and $R(x, a, 2)$

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So: $R(y, b, 2)$ and $R(x, a, 2)$ (and therefore $\neg R(y, b, 1)$ and $\neg R(x, a, 1)$)

Relevance

$R(k, j, s)$: parameter k is **relevant** when CFP j is in **state** $s \iff$

There is a summand that can be taken when $d_j = s$, that either

- **directly uses** k for its condition or action, or
- **indirectly uses** k to determine the value of a parameter that is relevant after taking the summand

$$X(a: \{1, 2\}, b: \{1, 2\}, x: D, y: D) =$$

$$\sum_{d: D} a = 1 \quad \Rightarrow \text{read}(d) \cdot X(2, b, d, y) \quad (1)$$

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So: $R(y, b, 2)$ and $R(x, a, 2)$ (and therefore $\neg R(y, b, 1)$ and $\neg R(x, a, 1)$)

If $\neg R(k, j, s)$, then k is **irrelevant** when j is in state s

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For $|D| = 5$: state space reduction from 60 to 36 states.

Correctness and effectiveness

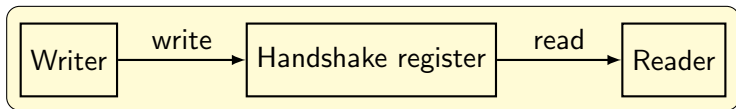
Theorem: correctness

The transformed LPE is strongly bisimilar to the original

Theorem: effectiveness

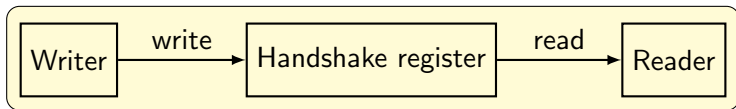
The number of reachable states of the transformed LPE is at most as large as the number of reachable states in the original

Case study: a handshake register



- **Recentness**
Any value read was at some point during reading the last value written
- **Sequentiality**
The values of sequential reads occur in the same order as they were written
- **Waitfree**
Completion of reads/writes in a bounded number of steps

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Building blocks:

- 4x safe register (random read during writing)
- 4x atomic boolean register

Verifying the implementation

- Model the handshake register **specification** as a μ CRL process
- Model the **implementation** as a μ CRL process
- **Generate** their **state spaces**
- **Minimise** with respect to some equivalence
- Check for **graph equivalence**

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Problem: **state space explosion**

Solution: **Apply stategraph!** (and compare to `parelm`)

Applying stategraph

	constelm states	parelm time (expl.)	constelm time (symb.)
$ D = 2$	540,736	0:23.0	0:04.5
$ D = 3$	13,834,800	10:10.3	0:06.7
$ D = 4$	142,081,536	–	0:09.0
$ D = 5$	883,738,000	–	0:11.9
$ D = 6$	3,991,840,704	–	0:15.4

	constelm states	stategraph time (expl.)	constelm time (symb.)
$ D = 2$	45,504	0:02.4	0:01.3
$ D = 3$	290,736	0:12.7	0:01.4
$ D = 4$	1,107,456	0:48.9	0:01.6
$ D = 5$	3,162,000	2:20.3	0:01.8
$ D = 6$	7,504,704	5:26.1	0:01.9

Other case studies

Other specifications stategraph was applied to:

- An Automatic In-flight Data Acquisition unit for a helicopter
- A cache coherence protocol for a distributed JVM
- The sliding window protocol
- An automatic translation from Erlang to μ CRL of a distributed resource locker in Ericsson's AXD 301 switch

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Results:

- Reductions in the number of states (up to 20 percent)
- Reductions in the number of parameters (up to 75 percent)
- Reductions in the number of summands (up to 25 percent)

Conclusions and Future Work

Conclusions:

- Novel method for **reconstructing control flow**
 - Even control flow hiding in state parameters is found
- Data flow analysis based on this control flow
 - Resetting variables that are no longer **relevant** (globally!)
 - **Decreases** in **states**, **parameters** and **summands**
 - Reductions obtained **before generating** the entire state space
- Precise **proofs** of **correctness** *and* **decrease of state space**
- Case studies show that **impressive results** are indeed obtained

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Future work:

- Investigate **additional applications** for the reconstructed control flow
 - Invariant generation
 - Visualisation (already implemented)
 - Improve confluence checking
- Use **more precise abstractions** based on control flow
- Apply these techniques to a probabilistic linear format

Questions

