# Saturation Enhanced with Conditional Locality: Application to Petri Nets

#### Vince Molnár<sup>1,2</sup>, István Majzik<sup>1</sup>

#### {molnarv,majzik}@mit.bme.hu

<sup>1</sup>Budapest University of Technology and Economics | Department of Measurement and Information Systems | Fault Tolerant Systems Research Group <sup>2</sup>Hungarian Academy of Sciences | MTA-BME Lendület Research Group on Cyber-Physical Systems







- Model checking
  - State space exploration
  - Property analysis
- Symbolic model checking
  - Characteristic function
  - Decision diagrams
  - Saturation algorithm
- In this paper...
  - Conditional locality
  - General representations
  - Enhanced saturation effect



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- Low-level formalism that preserves structure of high-level model
- A partitioned transition system (PTS) is a tuple  $(V, D, S^0, \mathcal{E}, \mathcal{N})$  s.t.:
  - V is the set of variables
  - *D* is the **domain** function  $(D(x_k) \subseteq \mathbb{N} \text{ for all } x_k \in V)$
  - $S^0 \subseteq \hat{S}$  is the set of **initial states** ( $\hat{S}$  is the potential state space)
  - E is the set of high-level events
  - $\mathcal{N} \subseteq \hat{S} \times \hat{S}$  is the **next-state relation** (function), partitioned by  $\mathcal{E}$  such that  $\mathcal{N} = \bigcup_{\alpha \in \mathcal{E}} \mathcal{N}_{\alpha}$
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  - Events are transitions
  - The next-state function is defined by weighted (inhibitor) arcs



#### **Decision Diagrams**

- Encoding sets: Quasi-reduced Ordered
  Multi-valued Decision Diagrams (MDD)
  - Nodes encode decisions (evaluation of a variable)
  - Arcs encode outcomes (values of a variable)
  - Terminal nodes encode result (0 or 1)
    - Arcs leading to 0 are not drawn
  - Ordered: same variable order on all paths
  - Quasi-reduced: no 2 nodes with the same children

#### Semantics:

- Each path from the root node to 1 encodes a tuple
- Components assume the values written on the arcs



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#### Semantics:

- Each path from the root node to 1 encodes a tuple
- Components assume the values written on the arcs
- Efficient recursive operations
  - Heavy caching

 $S(n_5) = \{(0,0,0), (1,0,0),$ 

()

 $n_{4}^{--}$ 

 $\mathbf{n}_2$ 

0

0

 $n_3$ 

0

0

(0,1,0), (0,0,1)

 $p_3$ 

 $\mathbf{p}_2$ 

 $p_1$ 

- General description of MDD-like next-state representations
- An Abstract Next-State Descriptor (ANSD) is a tuple (*D*, *lvl*, *next*):
  - D is the set of descriptors (≈MDD nodes) incl. terminal empty and identity;
  - $lvl : D \rightarrow \mathbb{N}$  is the **level** function (used to assign descriptors to variables);
  - next : D × N × N → D is the indexing function that computes a child descriptor one level lower from a (source, target) index pair
- Can be regarded as a common interface for...



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- Can be regarded as a common interface for...
  - Kroenecker matrices, matrix diagrams, MDDs with 2k levels, etc.



- Very simple representation for Petri nets:
  - Descriptors encode transition effect on a single place
  - $d = \langle W^{-}(t, p), W^{\circ}(t, p), W^{+}(t, p), d' \rangle$  (+terminal identity 1)
  - $next(d, i, j) = \begin{cases} d', & w^- \le i < w^\circ \land j = i w^- + w^+ \\ \mathbf{0}, & \text{otherwise} \end{cases}$



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## **Dependencies & Locality**

#### Basic dependencies between events and variables:

Locally invariant (–)	Locally read-only (r)	Locally read-write (rw)	
Value of variable does not affect the outcome of event	Value of variable does not change but affects outcome	Value of variable can be changed by the event	
	L		
		•	

	p <sub>1</sub>	p <sub>2</sub>	p <sub>3</sub>
I <sub>1</sub>	rw	r	r
I <sub>2</sub>	r	rw	r
l <sub>3</sub>	r	r	rw
f <sub>1</sub>	rw	_	-
f <sub>2</sub>	_	rw	_
f <sub>3</sub>	_	_	rw

NGARIAN



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I <sub>2</sub>	r	rw	r		$p_1$
l <sub>3</sub>	r	r	rw	_	
f <sub>1</sub>	rw	_	-		
f <sub>2</sub>	-	rw	-		VER A
f <sub>3</sub>	_	_	rw	f <sub>3</sub>	

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- Saturation is an algorithm for state space generation of PTSs
- Exploits locality to recursively compute the least fixed point  $S = S \cup \mathcal{N}(S)$  such that  $S^0 \subseteq S$ 
  - Equivalent to  $S^0 \cup \mathcal{N}(S^0) \cup \mathcal{N}(\mathcal{N}(S^0)) \cup \cdots = \mathcal{N}^*(S^0)$
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$f_1$	rw	_	-
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- Groups events based on the highest supporting variable
  - $Top(\alpha)$  is the highest supporting variable in the encoding MDD
  - $\mathcal{E}_k = \{ \alpha \mid Top(\alpha) = k \}$
  - $\mathcal{N}_k = \bigcup_{\alpha \in \mathcal{E}_k} \mathcal{N}_\alpha$
- Saturated MDD node n:
  - $S(n) = S(n) \cup \mathcal{N}_k(S(n))$  where k = lvl(n)
  - Children of n are saturated (0 and 1 are saturated)
- Starting from a node n encoding  $S(n) = S^0$ 
  - Recursively saturate children then compute fixed point

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In the final MDD:

only saturated nodes

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- Starting from a node n er
  - Recursively saturate child

Less intermediate nodes: better performance

In the final MDD:

only saturated nodes



# **Conditional Locality**

#### Additional dependency class between events and variables:

Locally invariant	Locally read-only Locally read-only		ad-write
Value of variable does not affect the outcome of event	Value of variable does not change but affects outcome	Value of variable can b changed by the event	
	Conditionally read-only		
Intuition:	For some values of some variables (guard) the event does not change the variable		

#### Saturation exploits that independent variables do not change when firing

- This might be true for supporting variables as well
  - Definitely true for read-only
  - Conditionally true for conditionally read-only
- In other words...
  - If an event is conditionally local on a variable, then it can be split s.t. one part is read-only and the other is read-write

Conditional

locality

## **Enhanced Saturation**

- Main idea:
  - Compute local fixed point with conditionally local events
  - Remember and cache the effect of higher (unaffected) variables
- Advantages:
  - Conditional *Top* values may be lower
  - Conditionally saturated nodes are more likely to be final
- Disadvantages:
  - The effect of higher variables must be remembered
  - (main motivation of constrained saturation)
- With an **ANSD representation** *d*:
  - next(d, i, i) is the conditionally local part (read-only on this level)
    - And the resulting descriptor d' encodes the effect of i on the event!
    - We can fire this part on a lower level any number of times
  - next(d, i, j) with  $i \neq j$  is the part we have to fire on this level



#### Example

	<b>p</b> <sub>1</sub>	p <sub>2</sub>	p <sub>3</sub>
I <sub>1</sub>	rw	r	r
l <sub>2</sub>	r	rw	r
l <sub>3</sub>	r	r	rw
f <sub>1</sub>	rw	-	-
f <sub>2</sub>	_	rw	-
f <sub>3</sub>	_	_	rw



Assume a variable ordering (p<sub>1</sub>, p<sub>2</sub>, p<sub>3</sub>)

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ACADEMY

(S) (RG)





### Example

	p <sub>1</sub>	p <sub>2</sub>	p <sub>3</sub>
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f <sub>2</sub>	-	rw	-
f <sub>3</sub>	-	_	rw



Assume a variable ordering (p<sub>1</sub>, p<sub>2</sub>, p<sub>3</sub>)

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- For saturation
  - Everything except  $f_1$  and  $f_2$  must be fired on top level



## Example

	p <sub>1</sub>	p <sub>2</sub>	p <sub>3</sub>
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f <sub>1</sub>	rw	-	-
f <sub>2</sub>	-	rw	-
f <sub>3</sub>	_	_	rw



- Assume a variable ordering (p<sub>1</sub>, p<sub>2</sub>, p<sub>3</sub>)
- For saturation
  - Everything except f<sub>1</sub> and f<sub>2</sub> must be fired on top level
- For saturation with conditional locality
  - $l_1$  and  $l_2$  can also be fired lower if enabled
  - (the fixed point iteration will not change  $p_2$  and/or  $p_3$ )



## **Details and Discussion**

- Modified saturation algorithm:
  - $Saturate(n) \rightarrow Saturate(n, d)$  Computes saturated node
    - Saturate now has next-state relation as a parameter (represented by an ANSD)
  - $SatRelProd(n, d) \rightarrow SatRelProd(n, d_{sat}, d_{fire})$ 
    - Relational product still gets next-state relation to fire  $(d \rightarrow d_{fire})$  image of event
    - Plus the next-state relation to saturate with (*d<sub>sat</sub>*, for conditionally local events)
    - Recursion: pass next(d, j, j) for d<sub>sat</sub> and next(d, i, j) for d<sub>fire</sub>
- A generalization of constrained saturation-based methods:
  - Events do not have to be partitioned anymore (), this is automatic
  - Contraints/priorities/synchronization can be directly encoded in the ANSD
- Overhead?
  - Cache fragmentation because of multiple possible *d* parameters
  - Offset by less MDD nodes created during saturation
  - Degrades to saturation without (conditionally) read-only dependencies

Computes

## **Details and Discussion**

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- A **generalization** of constrained saturation-based methods:
  - Events do not have to be partitioned anymore (), this is automatic
  - Contraints/priorities/synchronization can be directly encoded in the ANSD
- Overhead?

#### No real overhead expected for Petri nets

Token count may either enable or disable transition, value is not used elsewhere (only two possible child descriptors: d' and **0**)

Computes

- Implemented saturation (SA) and generalized saturation (GSA)
- Models: (almost) all 743 models from MCC (as of January 2019)
- Variable orders:
  - Generated with sloan algorithm (recommended by Amparore et al, 2018)



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  - Modified sloan leaving out read-only dependencies
- Which algorithm and which variable order?
  - Modified sloan vs. Sloan (MDD size, difference in 117 models)
    - Modified sloan smaller MDD: 69/117 larger MDD: 39/117
  - GSA with modified sloan vs. SA with sloan
    - GSA >2x faster: 78 models >2x slower: 16 models
- More research on (variable ordering, algorithm) pairs is needed

#### Summary

#### **Saturation Enhanced with Conditional Locality**

#### Conditional Locality

- Finer definition of event-variable dependencies
- Enhanced Saturation
  - No need to partition next-state relation (done automatically)
  - Generalization of constrained saturation-based approaches
  - Enhanced saturation effect may lead to better performance

#### **Application to Petri Nets**

- Evaluation on models of the MCC
  - Degrades to saturation without conditional locality
  - Often orders of magnitude faster
  - Virtually no overhead otherwise

#### Future work: investigate more general models (e.g., statecharts)

