

University of Utah

Explicit Algorithms for Probabilistic Model Checking

Igor Melatti





• Two explicit algorithms for probabilistic model checking are proposed



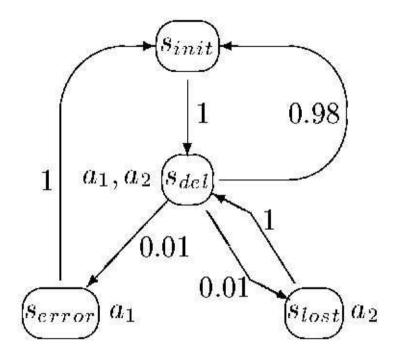
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 - Formal description
 - Proof of correctness
 - Implementation (FHP-Mur φ)



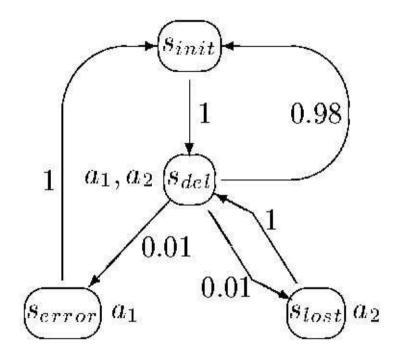
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 - * Verification of a "real-world" system
- Formal analysis of the proposed Markov Chain description language

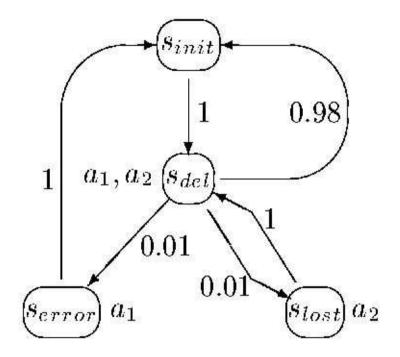


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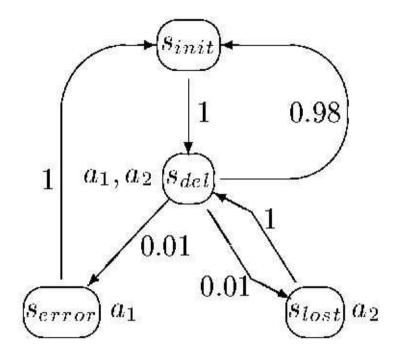
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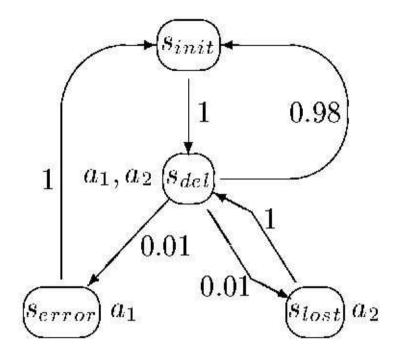
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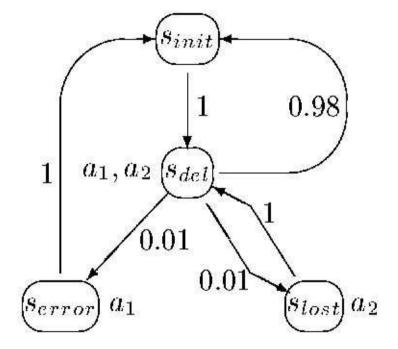
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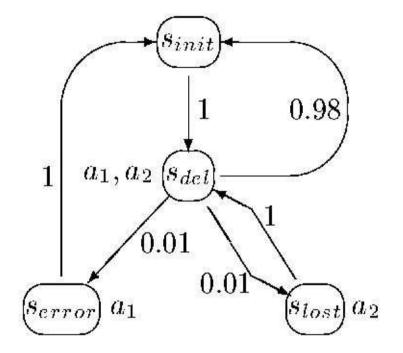
• Probability of a finite path ρ : $\mathbf{P}(\rho) = \prod_{i=0}^{|\rho|-1} \mathbf{P}(\rho(i), \rho(i+1)).$





Markov Chains

•
$$S = \{s_{init}, s_{del}, s_{lost}, s_{error}\}$$



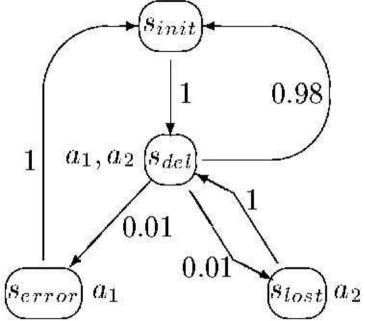
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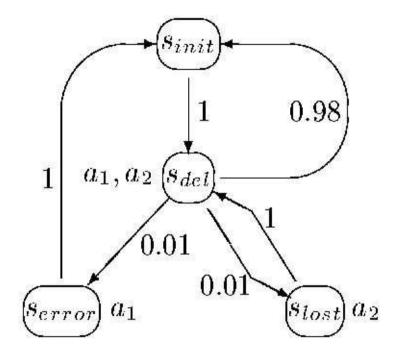
Since

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$$S = \{s_{init}, s_{del}, s_{lost}, s_{error}\}$$

• $\mathbf{P} = \begin{pmatrix} s_{init} & s_{del} & s_{lost} & s_{error} \\ 0 & 1 & 0 & 0 \\ 0.98 & 0 & 0.01 & 0.01 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix}$



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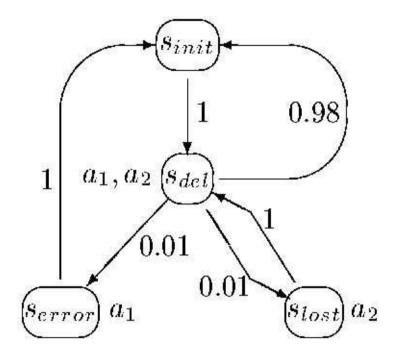
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• 2 possible paths and their probabilities:

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$$\mathbf{P}(s_{init}s_{del}s_{error}s_{init}) =$$

 $1 \cdot \frac{1}{100} \cdot 1 = \frac{1}{100}$
- $\mathbf{P}(s_{init}(s_{del}s_{lost})^k s_{del}s_{init}) =$
 $1 \cdot (\frac{1}{100} \cdot 1)^k \cdot \frac{98}{100} = \frac{98}{10^{2(k+1)}}$

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• Impossible path: $s_{init}s_{del}s_{error}s_{del}$





• Markov Chain analysis



- Markov Chain analysis
- Given the description of a Markov Chain, it verifies a PCTL property

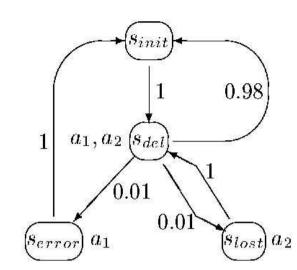


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- PCTL: Probabilistic CTL
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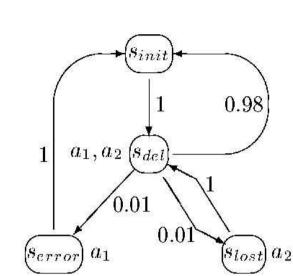


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- PCTL: Probabilistic CTL
 - [$tt \mathbf{U} (\neg \phi \land \neg [tt \mathbf{U}\phi]_{\geq 1})$] ≤ 0
- BPCTL: Bounded PCTL
 - Proper subset of PCTL
 - All Untils (U) must be bounded

$$- [tt \mathbf{U}^{\leq k_1} (\neg \phi \land \neg [tt \mathbf{U}^{\leq k_2} \phi]_{\geq 1})]_{\leq 0}$$
$$- [tt \mathbf{U}^{\leq k_1} (\phi_{und} \land \neg [tt \mathbf{U}^{\leq k_2} \neg \phi_{err}]_{\geq 1})]_{\leq 0}$$



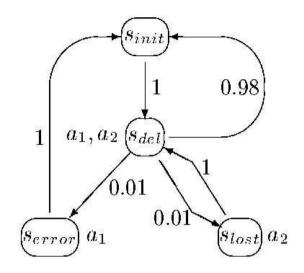
Property: [Try_to_deliver $U^{\leq 100}$ Correctly_delivered] ≥ 0.9



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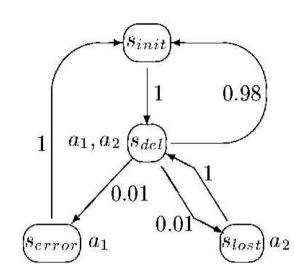
- Try_to_deliver (T in the following) is true if we are in state s_{del} or s_{lost}
- Correctly_delivered (C in the following) is true if we are in state s_{init}
- Initial state is s_{del}





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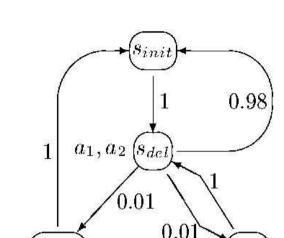
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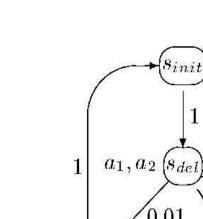
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 a_1

• Is the probability of the paths of the form $T^k C$ ($0 \le k \le 100$) at least 0.9?

 $s_{lost} a_2$

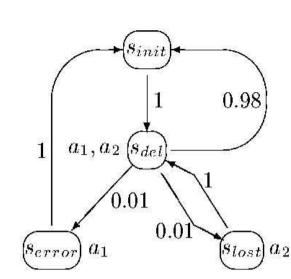
- A path of the form T^kC corresponds to an execution of the system in which, after a bounded trials, the message is finally transmitted
- Thus, we are requiring the probability of a "correct behavior" to be high enough (i.e. ≥ 0.9)



0.98

Property: $[Try_to_deliver U^{\leq 100} Correctly_delivered]_{\geq 0.9}$ • In a more mathematic speech, pick a path π at random, the probability that

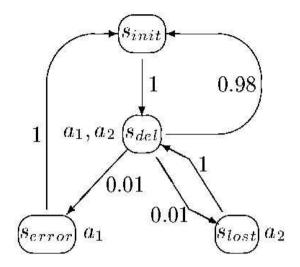
 $\pi = T^k C$ for some $k \leq 100$ has to be ≥ 0.9



Property: [Try_to_deliver $U^{\leq 100}$ Correctly_delivered] ≥ 0.9

- In a more mathematic speech, pick a path π at random, the probability that $\pi = T^k C$ for some k < 100 has to be ≥ 0.9
- In our framework, $P[T \ U^{\leq 100} \ C] = \sum_{\pi \mid \exists k \leq 100: \ \pi = T^k C} \mathbf{P}(\pi)$ holds





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 $\pi = T^k C$ for some $k \leq 100$ has to be ≥ 0.9

- In our framework, $P[T \ U^{\leq 100} \ C] = \sum_{\pi \mid \exists k \leq 100: \ \pi = T^k C} \mathbf{P}(\pi)$ holds
- \bullet Given a BPCTL formula $[\Phi]_{\geq 0.9},$ our algorithms computes $P[\Phi]=\sum_{\pi|\pi\models\Phi}\mathbf{P}(\pi)$



• Existing approaches to probabilistic model checking



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 - All based on symbolic computations



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 - If it is not, an exponential amount of RAM memory is needed
 - Our approach tries to avoid this, at least for some classes of Markov Chains





• Finite Horizon Probabilistic - Mur φ





• Explicit probabilistic model checker





- Finite^Horizon^Probabilistic^{-Mur φ}
- Explicit probabilistic model checker
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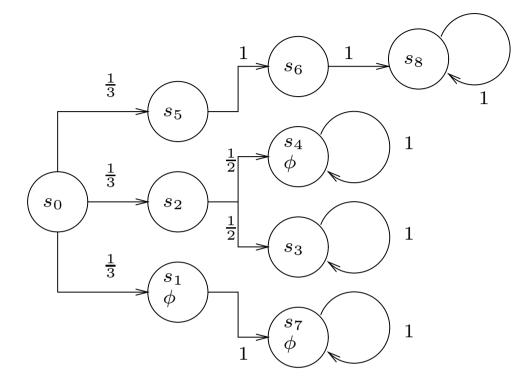




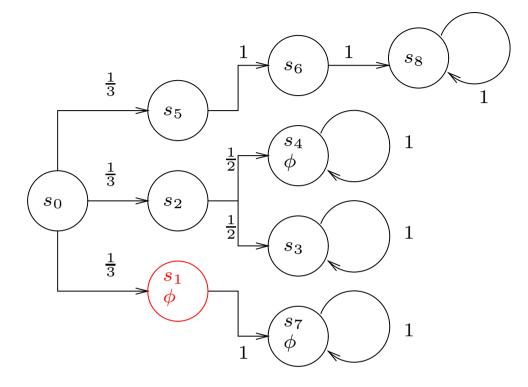
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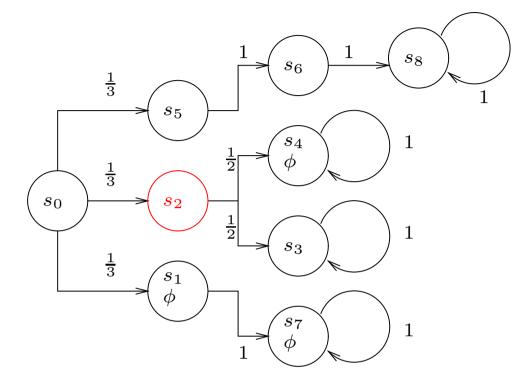
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 - explicit verification often outperforms symbolic verification in non-probabilistic model checking
 - we will show that this holds also for probabilistic model checking
- $\mathrm{Mur} \varphi$ modified in the input language and in the verification algorithm
- Two explicit algorithms developed
 - BF visit: only for finite horizon safety properties
 - * Able to compute error probabilities
 - DF visit: all BPCTL formulas



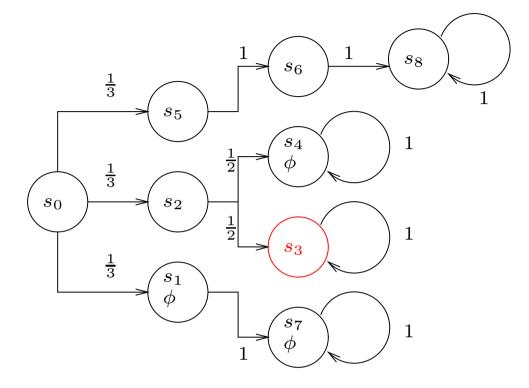
- We want to verify if $s_0 \models [tt \ \mathbf{U}^{\leq 2} \ \phi]_{\geq 0.5}$
- ϕ holds in s_1, s_4, s_7
- $\bullet\,$ The searched probability is: 0



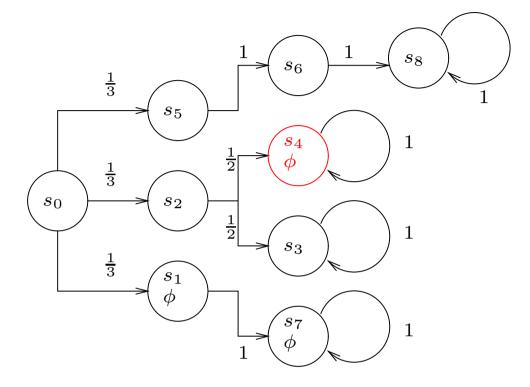
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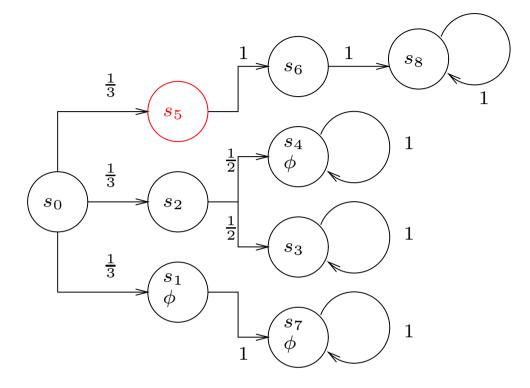
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- The searched probability is: $\frac{1}{3} + \frac{1}{3} \times \ldots$



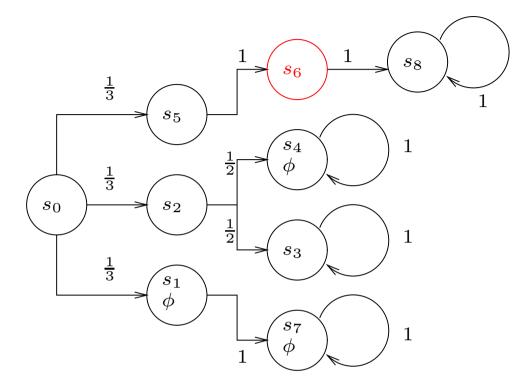
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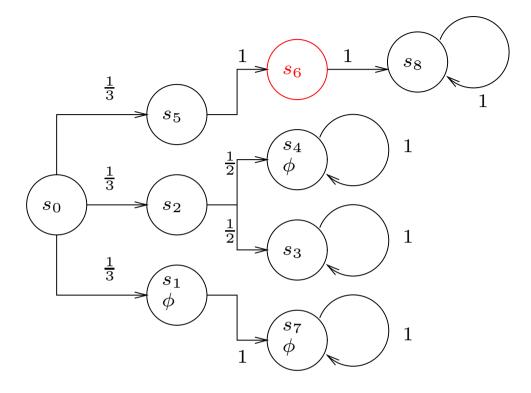
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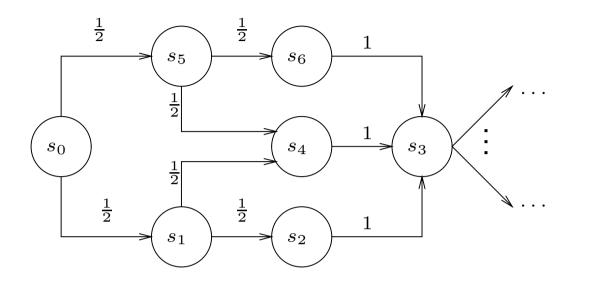


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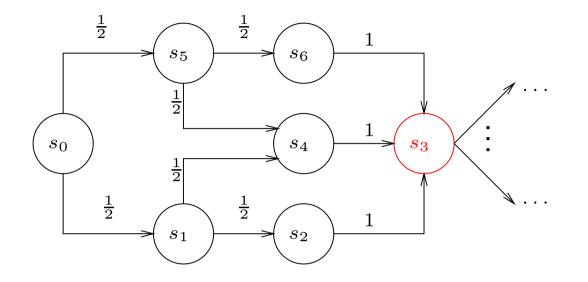
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- ϕ holds in s_1, s_4, s_7
- The searched probability is: $\frac{1}{3} + \frac{1}{3} \times \frac{1}{2} + \frac{1}{3} \times 0$
- Finally, we have $\frac{1}{3} + \frac{1}{3} \times \frac{1}{2} = \frac{1}{2} \ge 0.5$, so the property is verified





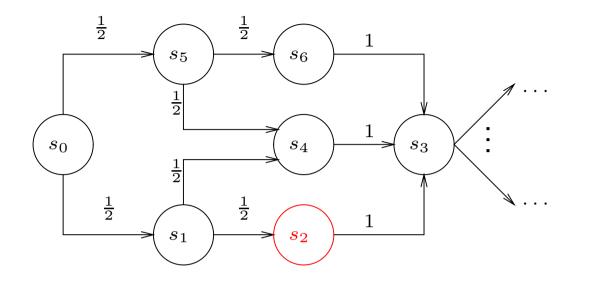
- We want to verify if $s_0 \models F$, being $F \equiv [\Phi \ \mathbf{U}^{\leq k} \ \Psi]_{\leq 0.5}$
- The cache stores 4-tuples $\{s, F, h, p\}$
 - p is the probability of $\Phi \ \mathbf{U}^{\leq h} \ \Psi$





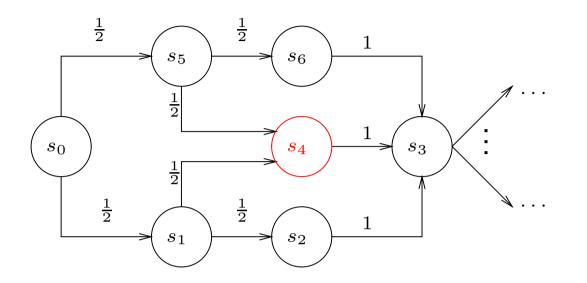
- When the DF visit of s_3 is completed, $\{s_3, F, k-3, p_3\}$ is inserted in the cache
 - p_{3} is the probability value computed by the DF on \boldsymbol{s}_{3}
 - k is decremented of 3 because s_3 is reached in 3 steps from s_0





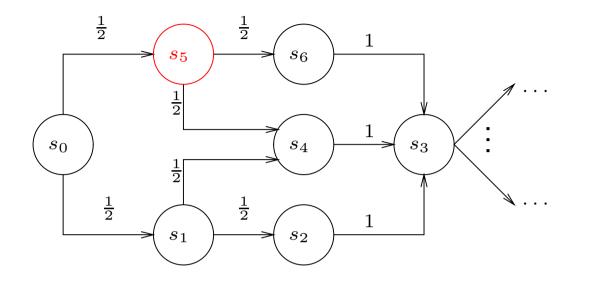
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 - p_3 is the probability value computed by the DF on s_3
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- Analogously, $\{s_2, F, k-2, p_2\}$ is inserted in the cache





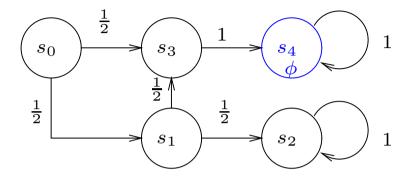
- In this way, the DF visit of s_4 can directly compute $p_4 = p_3 \times 1$
 - p_3 is not computed, but it is found on the cache
- Then, $\{s_4, F, k-2, p_4\}$ is inserted in the cache





- \bullet Analogously, when the DF visit of s_5 starts, the nested DF visit of s_4 is skipped
 - p_4 is not computed, but it is found on the cache
- The result of the DF visit of s_6 will be multiplied by $\frac{1}{2}$ and then added to $\frac{1}{2} \times p_4$



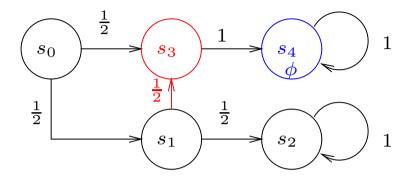


• We want to verify if $s_0 \models F$

-
$$F \equiv [tt \ \mathbf{U}^{\leq 2} \ \Phi]_{\leq 0}$$

- $\Phi \equiv [tt \ \mathbf{U}^{\leq 2} \ \phi]_{\geq 1}$
- $\phi(s_4) = 1, \forall s \neq s_4. \ \phi(s) = 0.$

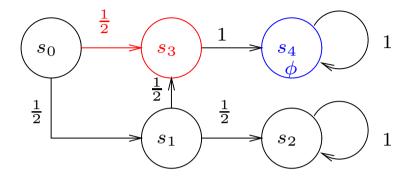




- We want to verify if $s_0 \models F$,
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 - $\Phi \equiv [tt \mathbf{U}^{\leq 2} \phi]_{\geq 1}$ $\phi(s_4) = 1, \forall s \neq s_4. \ \phi(s) = 0.$
- s_3 is visited for the first time as a successor of s_1
 - The 4-tuple $< s_3, \Phi, 1, 1.0 >$ is stored on the cache

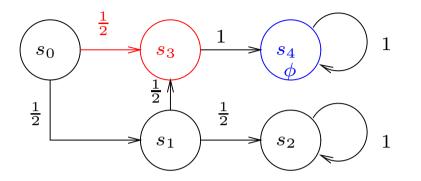






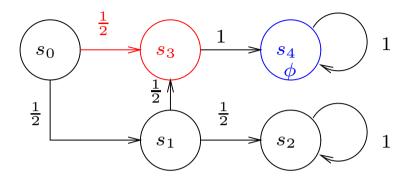
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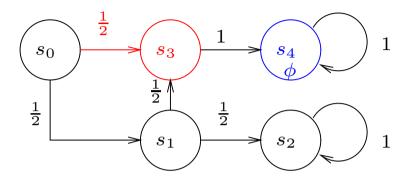
- s_3 is visited for the second time as a successor of s_0
 - The required 4-tuple $< s_3, \Phi, 2, p >$ is not on the cache





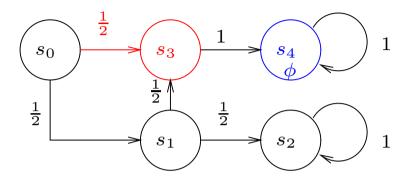
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 - The stored probability 1.0 is already in the right relation with the probability bound given in $\Phi \equiv [tt \ \mathbf{U}^{\leq 2} \ \phi]_{[\geq 1]}$





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 - So, the second DF visit on \boldsymbol{s}_3 is avoided





Probabilistic dining philosophers Pnueli-Zuck (PZ) and Lehmann-Rabin

(LR) protocols



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- Probabilistic Safety Verification
- Probabilistic Robustness Verification



NPHIL	MAX_WAIT	Result	Mur $arphi$ Mem (MB)	PRISM Mem (MB)	Mur $arphi$ Time (s)	PRISM Time (s)			
Modified Pnueli-Zuck									
5	3	false	5.0e+2	9.168246e+02	1.28381900e+04	1.196793e+03			
5	4	false	5.0e+2	N/A	1.27377300e+04	N/A			
Modified Lehmann-Rabin									
3	4	true	5.0e+2	7.014830e+01	5.00634000e+03	5.359870e+02			
4	3	true	5.0e+2	N/A	1.11480680e+05	N/A			

Property verified:

- If a philosopher risks to die, then it will eat soon
- $[tt \mathbf{U}^{\leq k_1} (\phi_{und} \land \neg [tt \mathbf{U}^{\leq k_2} \neg \phi_{err}]_{\geq 1})]_{\leq 0}.$

NPHIL, MAX_WAIT: protocol parameters





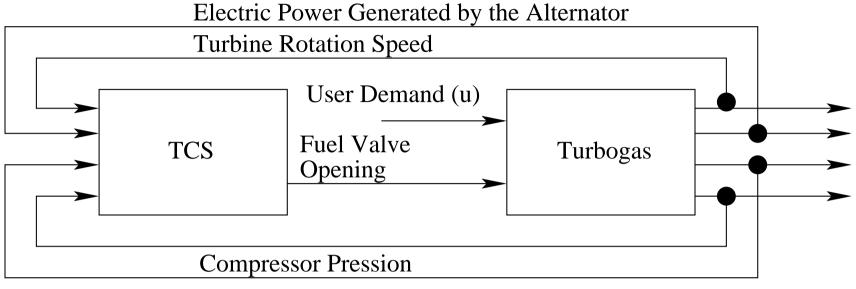
 ICARO: 2MW Electric Co-generative Power Plant, in operation at the ENEA Research Center of Casaccia (Italy)



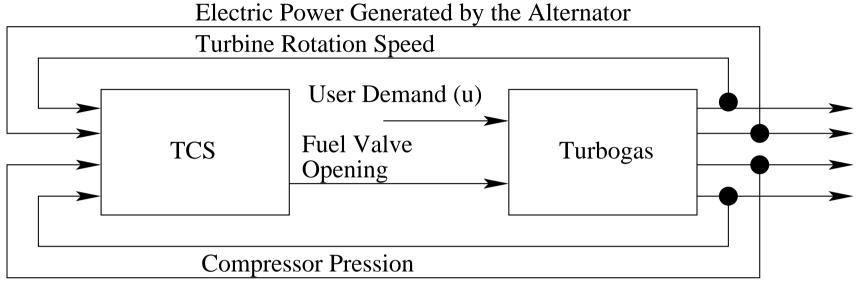
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- The most important module is the Turbogas Control System (TCS)
 - It is also the most complex one
- It is an hybrid system: it has both continuous (e.g., power and user demand) and discrete variables (execution modality)
 - This kind of systems are hard to analyze with OBDD-based model checkers
 - Thus, there is no hope to verify TCS with PRISM

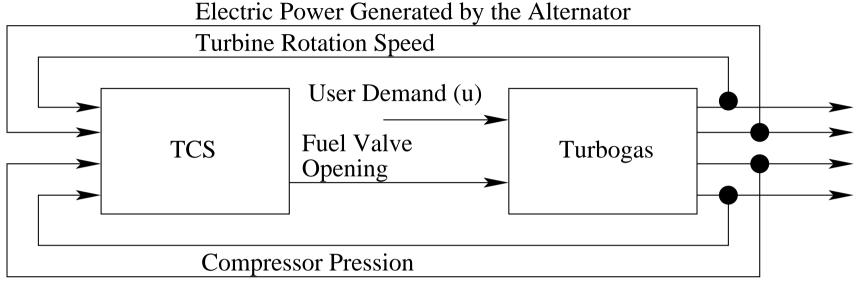


Exhaust Smokes Temperature



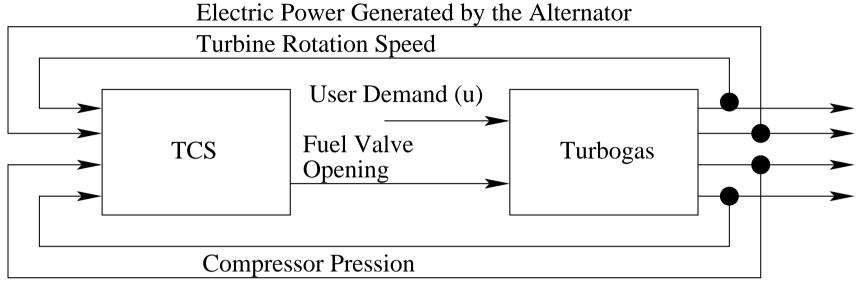
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Exhaust Smokes Temperature

- TCS is an electronic circuit, its detail are known
- The turbogas is modeled by a set of ODEs
- The user demand is modeled as a nondeterministic disturbance
 - Its variation is bounded by a verification parameter (MAX_D_U)





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 - This has to hold for every value of the user demand
- As a result, if the user demand varies too much rapidly (i.e. MAX_D_U is too high), the controller fails





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- Let
$$p(u,i) = \begin{cases} 0.4 + \beta \frac{(u-\frac{M}{2})|u-\frac{M}{2}|}{M^2} & \text{if } i = -1\\ 0.2 & \text{if } i = 0\\ 0.4 + \beta \frac{(\frac{M}{2}-u)|u-\frac{M}{2}|}{M^2} & \text{if } i = +1 \end{cases}$$



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$$u(t+1) = \begin{cases} \max(u(t) - \alpha, 0) & \text{with prob. } p(u(t), -1) \\ u(t) & \text{with prob. } p(u(t), 0) \\ \min(u(t) + \alpha, M) & \text{with prob. } p(u(t), +1) \end{cases}$$



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MAX_D_U	Reachable States	Finite Horizon	CPU Time	Probability
25	3018970	1600	68562.570	7.373291768e-05
35	2226036	1400	50263.020	1.076644427e-04
45	1834684	1300	41403.150	9.957147381e-05
50	83189	900	2212.360	3.984375e-03



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- k_1 is sufficient to reach an undesired state
- $k_2 = \frac{k_1}{100}$

MAX_D_U	Visited States	k_1	CPU Time (s)	Probability
35	1.159160e+05	800	3.702400e+03	4.104681e-03
45	4.098000e+04	700	1.313900e+03	1.792883e-02
50	4.067700e+04	700	1.307850e+03	3.825000e-02

Results on a machine with 2 processors (both INTEL Pentium III 500Mhz) and 2GB of RAM. Mur φ options used: -m500 (use 500 MB of RAM)









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Improving performances

• Try to apply symmetry reduction (to be investigated)