# Mean-Payoff Optimization in Continuous-Time Markov Chains with Parametric Alarms

Christel Baier Clemens Dubslaff Ľuboš Korenčiak Antonín Kučera Vojtěch Řehák

IFIP WG 2.2 2017 Meeting, Bordeaux

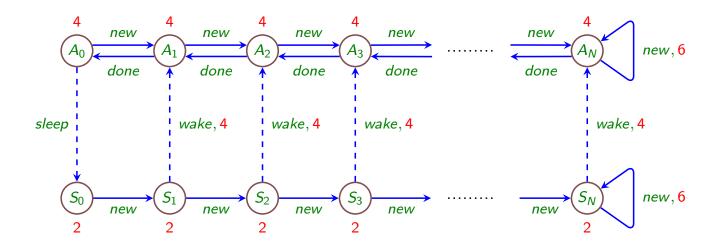
Antonín Kučera

Mean Payoff in CTMC with Alarms

IFIP WG 2.2 2017

1 / 10

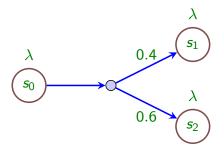
#### Dynamic power management of a disk drive



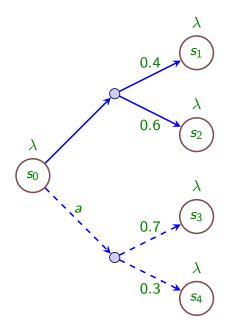
 What timeout values achieve the minimal long-run average power consumption?

## CTMC with parametric alarms (1)

"Ordinary" CTMC



CTMC with alarms  $\{a_1, \ldots, a_n\}$ 



Antonín Kučera

Mean Payoff in CTMC with Alarms

IFIP WG 2.2 2017

3 / 10

## CTMC with parametric alarms (2)

- In CTMC with parametric alarms  $\{a_1, \ldots, a_n\}$ , the distributions associated to  $\{a_1, \ldots, a_n\}$  are not fixed but parameterized by a single parameter.
- Restrictions:
  - At most one alarm is active in each state.
  - Each alarm is set in precisely one state.
- After fixing the parameters, we obtain a fully stochastic CTMC with alarms.
- Can we compute parameter values achieving  $\varepsilon$ -optimal mean-payoff?

#### Computing $\varepsilon$ -optimal parameter values

- 1. Given a CTMC with parametric alarms and  $\varepsilon > 0$ , we compute a discretization constant  $\kappa > 0$  such that  $\varepsilon$ -optimal parameter values are among the (finitely many)  $\kappa$ -discretized values.
- 2. We construct a semi-Markov decision process  $\mathcal{M}$  where the actions correspond to discretized parameter values. Thus, the original problem reduces to computing an optimal strategy for  $\mathcal{M}$ .
- 3. The set of states of  $\mathcal{M}$  is small but the number of actions is very large. We employ a symbolic technique which avoids the explicit construction of these actions.

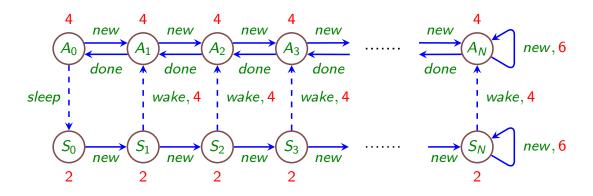
Antonín Kučera

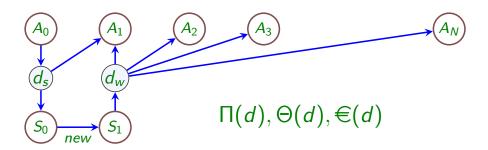
Mean Payoff in CTMC with Alarms

IFIP WG 2.2 2017

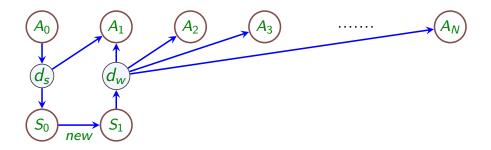
5 / 10

## Computing $\varepsilon$ -optimal parameter values (2)





## Computing $\varepsilon$ -optimal parameter values (3)



- ullet An optimal for  ${\mathcal M}$  can be computed by strategy iteration.
- Each action d is ranked by a function F(d) depending on  $\Pi(d)$ ,  $\Theta(d)$ , and  $\Theta(d)$ . The goal is to find an action with minimal F(d).
- We express F(d) analytically, compute its derivative, and consider only a small set of actions close to the local minima of F(d).
- Applicable to alarms with Dirac (fixed-delay), uniform, and Weilbull distributions.

Antonín Kučera

Mean Payoff in CTMC with Alarms

IFIP WG 2.2 2017

7 / 10

## Experiments (disk drive example)

- We considered  $N \in \{2, 4, 6, 8\}$ ,  $\varepsilon \in \{0.1, 0.01, 0.001, 0.0005\}$ .
- The upper and lower bounds for the timeouts were 0.1 and 10 time units, respectively.
- The required discretization step ranges from  $10^{-25}$  to  $10^{-19}$ .

# Experiments (disk drive example), cont.

N	ε	creating	solving	poly
		time [s]	time [s]	degree
2	0.1	0.15	0.24	46
	0.01	0.15	0.25	46
	0.001	0.16	0.28	53
	0.0005	0.16	0.33	53
4	0.1	0.14	0.25	46
	0.01	0.16	0.25	46
	0.001	0.16	0.28	53
	0.0005	0.16	0.33	53
6	0.1	0.16	0.35	46
	0.01	0.16	0.35	46
	0.001	0.17	0.40	53
	0.0005	0.18	0.43	53
8	0.1	0.19	0.35	46
	0.01	0.19	0.35	46
	0.001	0.20	0.43	53
	0.0005	0.22	0.44	53

Antonín Kučera

Mean Payoff in CTMC with Alarms

IFIP WG 2.2 2017

9 / 10

# Limitations, future work

- Each alarm has to be set in precisely one state. Hence, we cannot model systems of concurrently running components. POMPD techniques might help?
- Other objectives?
- Multi-criteria parameter optimizations.