Quantitative evaluation of non-Markovian stochastic models

Enrico Vicario

Lab. of Software Technologies - Dept. of Information Engineering - University of Florence from joint work with: M.Biagi, L.Carnevali, A.Horvath, M.Paolieri

TU Wien - January 24, 2018

this is about:

- stochastic models and processes,... and non-Markovian processes,
- and their quantitative evaluation
- ... through the method of stochastic state classes and the Oris tool
- with a few examples of application
- a technical talk interleaved with:
 - ground concepts of the research in quantitative evaluation

Outline



- stochastic models and processes
- classes of the underlying stochastic process of a model
- Markov Regenerative Processes MRP
- 2 the method of stochastic state classes and the Oris tool
 - the method of stochastic state classes
 - the Oris tool
 - examples of application

map of concepts: Models, Processes, and quantitative evaluation

- a model uses some formalism to capture a case in some reality
- a fully stochastic model identifies one single probability space
- ... on which we can define multiple stochastic processes and rewards
- ... amenable to solution to evaluate various quantities of interest



a few questions:

- what are models for?
 - early assessment of design choices
 - model driven guidance and insight for implementation, integration and operation stages
 - not only for SW intensive systems, but also for mechanics, physics, ... economics, social sciences, ... life sciences ...
- what is a stochastic model?
 - a *non-deterministic* model specifies an experiment allowing multiple outcomes
 - a stochastic model gives the space of outcomes a measure of probability
 - note: "stochastic" derives from the Greek word "stokhasticos", meaning able to guess, which in turn derives from "stokhos", meaning a stick target that an archer aims to shoot at
- why should a model be stochastic?
 - intrinsic stochastic behavior, by nature or by design
 - epistemic uncertainty, by abstraction
- what specific kind of stochastic model are we here dealing with ?
 - concurrent models
 - stochastic in choices e in durations
 - for systems that are supposed to meet real time requirements despite intertwined effects of concurrency and stochastic timing

stochastic models and processes

classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

more concretely, what is a model? and what is a formalism?

- Kublai Khan: But which is the stone that supports the bridge?

 Marco Polo: The bridge is not supported by one stone or another, but by the line of the arch that they form.

 Kublai Khan: Why do you speak to me of the stones? It is only the arch that matters to me.
- Marco Polo: Without stones there is no arch.

Italo Calvino, Invisible Cities, 1978.

stochastic models and processes classes of the underlying stochastic process of a mo Markov Regenerative Processes - MRP

... about the Formalism and the Model - 1/2

- stochastic Time Petri Nets (sTPN): a class of SPNs with generally distributed durations
 - places encode state conditions, true if at least one token
 - transitions encode events, enabled if all input conditions are true
 - at firing, move tokens from input to output places and sample a time to fire for each newly enabled transition
 - delay from enabling to firing is a random variable



a cycle of two step failure, detection delay, repair and restart as new

stochastic models and processes classes of the underlying stochastic process of a mod Markov Regenerative Processes - MRP

... about the Formalism and the Model - 1/2

- stochastic Time Petri Nets (sTPN): a class of SPNs with generally distributed durations
 - · places encode state conditions, true if at least one token
 - transitions encode events, enabled if all input conditions are true
 - at firing, move tokens from input to output places and sample a time to fire for each newly enabled transition
 - delay from enabling to firing is a random variable



• a cycle of two step failure, detection delay, repair and restart as new

stochastic models and processes classes of the underlying stochastic process of a mo Markov Regenerative Processes - MRP

... about the Formalism and the Model - 1/2

- stochastic Time Petri Nets (sTPN): a class of SPNs with generally distributed durations
 - places encode state conditions, true if at least one token
 - transitions encode events, enabled if all input conditions are true
 - at firing, move tokens from input to output places and sample a time to fire for each newly enabled transition
 - delay from enabling to firing is a random variable



a cycle of two step failure, detection delay, repair and restart as new

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

... about the Formalism and the Model - 1/2

- stochastic Time Petri Nets (sTPN): a class of SPNs with generally distributed durations
 - places encode state conditions, true if at least one token
 - transitions encode events, enabled if all input conditions are true
 - at firing, move tokens from input to output places and sample a time to fire for each newly enabled transition
 - delay from enabling to firing is a random variable



• a cycle of two step failure, detection delay, repair and restart as new

stochastic models and processes classes of the underlying stochastic process of a mo Markov Regenerative Processes - MRP

... about the Formalism and the Model - 1/2

- stochastic Time Petri Nets (sTPN): a class of SPNs with generally distributed durations
 - places encode state conditions, true if at least one token
 - transitions encode events, enabled if all input conditions are true
 - at firing, move tokens from input to output places and sample a time to fire for each newly enabled transition
 - delay from enabling to firing is a random variable



a cycle of two step failure, detection delay, repair and restart as new

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

- ... compose with time-triggered rejuvenation to increase reliability¹
- ... and to let concurrency appear



¹ (tweaked from:) S.Garg, A.Puliafito, M.Telek, K.S.Trivedi, "Analysis of software rejuvenation using Markov regenerative stochastic Petri net," Software Reliability Engineering, 1995.

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

- ... compose with time-triggered rejuvenation to increase reliability¹
- ... and to let concurrency appear



¹ (tweaked from:) S.Garg, A.Puliafito, M.Telek, K.S.Trivedi, "Analysis of software rejuvenation using Markov regenerative stochastic Petri net," Software Reliability Engineering, 1995.

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

- ... compose with time-triggered rejuvenation to increase reliability¹
- ... and to let concurrency appear



¹ (tweaked from:) S.Garg, A.Puliafito, M.Telek, K.S.Trivedi, "Analysis of software rejuvenation using Markov regenerative stochastic Petri net," Software Reliability Engineering, 1995.

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

- ... compose with time-triggered rejuvenation to increase reliability¹
- ... and to let concurrency appear



¹ (tweaked from:) S.Garg, A.Puliafito, M.Telek, K.S.Trivedi, "Analysis of software rejuvenation using Markov regenerative stochastic Petri net," Software Reliability Engineering, 1995.

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

- ... compose with time-triggered rejuvenation to increase reliability¹
- ... and to let concurrency appear



¹ (tweaked from:) S.Garg, A.Puliafito, M.Telek, K.S.Trivedi, "Analysis of software rejuvenation using Markov regenerative stochastic Petri net," Software Reliability Engineering, 1995.

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

- ... compose with time-triggered rejuvenation to increase reliability¹
- ... and to let concurrency appear



¹ (tweaked from:) S.Garg, A.Puliafito, M.Telek, K.S.Trivedi, "Analysis of software rejuvenation using Markov regenerative stochastic Petri net," Software Reliability Engineering, 1995.

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

- ... compose with time-triggered rejuvenation to increase reliability¹
- ... and to let concurrency appear



¹ (tweaked from:) S.Garg, A.Puliafito, M.Telek, K.S.Trivedi, "Analysis of software rejuvenation using Markov regenerative stochastic Petri net," Software Reliability Engineering, 1995.

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

- ... compose with time-triggered rejuvenation to increase reliability¹
- ... and to let concurrency appear



¹ (tweaked from:) S.Garg, A.Puliafito, M.Telek, K.S.Trivedi, "Analysis of software rejuvenation using Markov regenerative stochastic Petri net," Software Reliability Engineering, 1995.

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

skip: details about stochastic Time Petri Nets (sTPN)

$$sTPN = \langle P, T, A^{-}, A^{+}, A^{\bullet}, m_{0}, EFT, LFT, \tau_{0}, \mathcal{F}, \mathcal{W} \rangle$$

- (PN) concurrency, discrete locations, token moves: places *P*, transitions *T*, initial marking m_0 , arcs A^- , A^+ , A^\bullet
- (TPN) non-deterministic timed behavior, min-max durations, times to fire: earliest and latest firing times *EFT*, *LFT*, initial times to fire τ_0

(sTPN) (fully) stochastic timed behavior: probability density functions \mathcal{F} for transition durations discrete probabilities \mathcal{W} for ties among transitions with equal time-to-fire



... and convenience extensions ... as usual

skip: details about the Probability Space, and its relation with the Formalism

• an sTPN (with an initial state) identifies a probability space

 $\langle \Omega, \mathcal{F}, \mathbb{P} \rangle$

- the set of outcomes Ω is determined by the underlying TPN
 - (an outcome is an infinite run of the model)
 - Petri Net structure + duration supports
- the measure of probability $\mathbb P$ also depends on stochastic parameters
 - continuous distribution for transition firing times (\mathcal{F})
 - discrete distribution for choices among transitions with equal firing times (\mathcal{W})



map of concepts: Models, Processes, and quantitative evaluation

- a model uses some formalism to capture a case in some reality
- a fully stochastic model identifies one single probability space
- ... on which we can define multiple stochastic processes and rewards
- ... amenable to solution to evaluate various quantities of interest



stochastic models and processes

classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

... about Stochastic Processes, and the marking process



• a special underlying Stochastic Process: Marking Process

$$\mathbb{M} := \{ M(t), t \in \mathbb{R}_{\geq 0} \}$$

- some Rewards: trade-off between Reliability and Availability
 - unReliability (Ko);
 - unAvailability (Ko ∨ Detected ∨ Rej);
 - "added" unAvailability

 $(Ok \land Rej).$

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

... about Solution



 Rewards: unReliability (Ko); unAvailability (Ko ∨ Detected ∨ Rej); "added" unAvailability (Ok ∧ Rej)



stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

question: what are we actually doing when we solve a Model?

- the Model identifies a Probability Space
- a Reward specifies a Stochastic Process referred to the Marking Process
- ... so as to capture some Quantity of Interest for the Case
- and the Process is analyzed on the ground of mathematics
- ... using a SW tool

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

map of concepts: Durations and process Classes

- the underlying Stochastic Process of a Model is amenable to different solution techniques
- ... depending on its Class
- ... which in turn depends on the type of Durations and their concurrency



stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

remark: which calls into play the Exponential Random Variable

 apparently, *EXP*(λ) is just a Random Variable with exponential Probability Density Function (PDF):

$$f_X(t) = \lambda \cdot exp^{-\lambda \cdot t}$$
 $t \in \mathbb{R}_{\geq 0}$

• conversely, $EXP(\lambda)$ is uniquely marked by the *memoryless* property:

if X := EXP(lambda), Y := X|X > k, Z := Y - k THEN X = Z

• a direct consequence of a basic property of the exponential function:

$$exp^{t_1+t_2} = exp^{t_1} * exp^{t_2}$$

with major practical implications on expressivity and analyzability ...

remark: ... and the Markov Condition

- the Markov condition extends the memoryless property from Random Variables to Stochastic Processes
- "the future depends on the past only through the current marking"
 - so that prediction can get rid of the past history and its timing
- formally: the most recent observation of the marking *m* (at time t₀) subsumes any previous one (at times t₋₁,...t_{-N}):

 $\begin{aligned} & \textit{Prob}\{m(t_1)|m(t_0)\} = \textit{Prob}\{m(t_1)|m(t_0), m(t_{-1}), ...m(t_{-N})\} \\ & \forall N, \ \forall t_1 \ge t_0 \ge t_{-1} ... \ge t_{-N} \end{aligned}$



remark: on the overloaded meaning of the term "state"

- in the operational semantics of a model, and more generally in most branches of Engineering state is any abstraction sufficient to get rid of the past history
- the state of a stochastic process is the value of "a" Random Variable,
- ... which in turn can be any function on the space of outcomes
- the Markov condition means: the process state is also a model state
- renewal argument: decompose a run across a time point (a kind of compositionality)



stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

Continuous Time Markov Chain (CTMC)

 if the model includes only IMM or EXP transitions, due to the memoryless property of EXP, the marking process always satisfies the Markov condition



- the (right-continuous) marking process is thus a Continuous Time Markov Chain (CTMC)
 - characterized by a constant Infinitesimal Generator Q
 - solution through efficient and mature techniques

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

... about the Process Class: non-Markovian models

- ... but, models may include generally distributed (GEN) durations
 - break the limit of memoryless exponential (EXP) distributions
 - possibly with bounded support
 - (transition colors: white for EXP, black for GEN, gray for DET)



- may become relevant for validity in various application contexts
 - aging processes accumulating memory over time
 - real time systems with firm deadlines, bounded timeframes, synchronous releases, watchdogs, ...
 - timed protocols, signalling, ...

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

duration distributions matter - all EXP with DET clock

• change durations to EXP (with same mean), keeping the DET clock:



stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

duration distributions matter - all EXP with Erl(5) clock

 if also the DET clock is changed into a sequence of 5 EXP (Erlang with the same expected value), ripples are completely lost



• (on the meaning of steady state and mixing time in a stochastic process)

Memory and regeneration

- if the model includes GEN transitions, the marking is in general not a sufficient model state
- yet, at some points, the marking can be sufficient to characterize future behavior
- call these regeneration points



the process class depends on how regeneration points are encountered²



²GF.Ciardo, R.German, C.Lindemann, "A characterization of the stochastic process underlying a stochastic Petri net," IEEE TSE, 1994.

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

Semi-Markov Process (SMP) -1/2

 if GEN transitions never persist through any firing the underlying stochastic process regenerates at every step (yet, memory is accumulated during sojourn)



• Global Kernel G_{ij}(t): the first step from *i* is before t and reaches j

 $t_1 :=$ time of the first step $G_{ij}(t) := Prob\{(t_1 < t) \land (m(t_1) = j) | m(t_0) = i \land t_0 = 0\}$

• Holding time $H_i(t)$: the first step from *i* is after *t*

$$H_i(t) := Prob\{t_1 > t | m(t_0) = i \land t_0 = 0\}$$

• solved through a set of Volterra integral equations of the 2nd type:

$$\pi_{ij}(t) = H_i(t) \cdot \delta_{ij} + \sum_k \int_0^t \frac{dG_{ik}(x)}{dx} \pi_{kj}(t-x) dx$$

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

Semi-Markov Process (SMP) - 2/2

• global kernel and holding time derived directly from the model



- ... and Volterra equation solved by numerical integration
- but, no memory across subsequent locations

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

Markov Regenerative Process (MRP)

 always, wp1, the process eventually reaches a regeneration (possibly through infinite steps or in unbounded time)



• much more expressive, and actually sufficient for most purposes

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

MRP: kernels and generalized Markov renewal equations

- an MRP is characterized by 2 kernels L(t) and G(t)
- Local Kernel L_{ih}(t): starting from i, at t the state is h, and no regeneration occurred yet

 $t_1 :=$ time of the first regeneration $L_{ih}(t) := Prob\{(t_1 > t) \land (m(t) = h) | m(t_0) = i \land t_0 = 0\}$

• Global Kernel *G_{ij}(t*): starting from *i*, the first regeneration is before *t* and leads to *j*

 $G_{ij}(t) := Prob\{(t_1 < t) \land (m(t_1) = j) | m(t_0) = i \land t_0 = 0\}$

 transition probabilities can be derived by numerical integration of a set of integral equations (Volterra, 2nd type)

$$\pi_{ii}(t) = L_{ii}(t) + \sum_{k} \int_{0}^{t} \frac{dG_{ik}(x)}{dx} \pi_{ki}(t-x) dx$$

(generalized Markov renewal equations)

• ... but, how to get the kernels?

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

MRP: the special case of the enabling restriction

- if at most one GEN transition is enabled in any tangible marking
 - GEN transitions never persist to each other
 - the process subordinated to the activity period of a GEN is a CTMC, and kernels can thus be evaluated by uniformization ^{3 4 5}



• ... but, bad news for expressivity: no concurrent overlapping GEN timers

³GF.Ciardo, R.German, C.Lindemann, "A characterization of the stochastic process underlying a stochastic Petri net," IEEE TSE, 1994.

⁴A.Bobbio, M.Telek, "Markov regenerative SPN with non-overlapping activity cycles,"IPDS95.

⁵H.Choi, V.G.Kulkarni, K.S.Trivedi, "Markov Regenerative stochastic Petri Nets," PEVA'94.

stochastic models and processes classes of the underlying stochastic process of a model Markov Regenerative Processes - MRP

on the frontier of MRP

• the class of MRP is much wider than the enabling restriction



a "recent" approach

- the method of stochastic state classes
 - multiple concurrent GEN, possibly over bounded supports
 - best fitting the case of "bounded regeneration"
- main concepts
 - compute probability densities over DBM zones that represent continuous sets of reachable states
 - add an age clock to enable transient analysis
 - restrain transient analysis within regeneration epochs, to evaluate local and global kernels, and then resort to Markov Renewal Theory
- implemented in the Oris tool and API

the method of stochastic state classes the Oris tool examples of application

a step back to the underlying non-deterministic TPN

 a finite sequence of transitions ρ := s₀ : t₀ → t₁... → t_n can be executed with a continuous multivariate set of timings {τ₁, τ₂...τ_n}



- call state class S_n the set of states reached after *n* steps along ρ
 - a common marking m_n, but a set D_n of different vectors of remaining times
 - the set D_n has the shape of a Difference Bounds Matrix (DBM) Zone 6 7 8 9
 - efficient (polynomial) symbolic encoding and manipulation

⁶D. L. Dill, "Timing assumptions and verification of finite-state concurrent systems," 1989

⁷B.Berthomieu, M.Diaz, "Modeling and verification of time dependent systems using TPNs"TSE91.

⁸J. Bengtsson, K. Larsen, F. Larsson, P. Pettersson, and W. Yi, "UPPAAL - A tool suite for automatic verification of real-time systems," 1996.

⁹E.Vicario, "Static Analysis and Dynamic Steering of Time-Dependent Systems Using TPNs, "TSE01

the method of stochastic state classes the Oris tool examples of application

compute probabilities over DBM zones



- stochastic state class Σ =< M, D, f() >
 - decorates each state class < M_n, D_n > with the joint prob. density function f_n() of times to fire of enabled transitions, as observed when the class is entered



10

¹⁰E.Vicario, L.Sassoli, L.Carnevali, "Using Stochastic State Classes in Quantitative Evaluation of Dense-Time Reactive Systems", IEEE TSE 2009

the method of stochastic state classes the Oris tool examples of application

skip: calculus of stochastic classes - 1/2

assume that transitions are initially newly enabled



 ... their times to fire are distributed independently, in product form, according to their static density function



the method of stochastic state classes the Oris tool examples of application

skip: calculus of stochastic classes - 2/2

• starting from a product form over a hyper-rectangle ...



• ... the assumption that *t*₁ fires first restricts the support and uniformly conditions probabilities



• ... at the firing of t_1 , a random time has elapsed

 remaining times to fire of persistent transitions t₂ and t₃ become dependent, and supported over a Difference Bounds Matrix (DBM) zone



the method of stochastic state classes the Oris tool examples of application

calculus of stochastic classes

- when subsequent transitions occur, supports remain in the shape of a Difference Bounds Matrix (DBM) zone
 - density functions are continuous piecewise multivariate functions over a partition in DBM sub-zones, continuous across internal borders



 closed form symbolic derivation for models with EXP, IMM, DET, and ExPol transitions (with possibly bounded support) ¹¹

$$f_t^s(x) = \sum_k^{\kappa} c_k x^{\alpha_k} e^{-\lambda_k x}$$
 for $x \in [EFT_t^s, LFT_t^s,]$

- implementation amounts to joint symbolic enumeration of DBM domains and analytical form of multi-variate joint density functions
 - intertwining due to zone difference constraints (linear, slope 1)

¹¹L.Carnevali, L.Grassi, E.Vicario, "State-density functions over DBM domains in the analysis of non-Markovian models," TSE'09.

measures enabled by stochastic state classes

• the probability that t₂ fires first (transition probability) is the integral over a DBM subset of the DBM zone

$$\mathsf{Prob}\{t_1 \ \mathsf{fires}\} = \int_{D \land (\tau(t_2) \le \tau(t_n) \ \forall n)} f_{\underline{\tau}}(\underline{x}) d\underline{x}$$

• the probability to reach a class is the product of transition probabilities on the path from the root



the method of stochastic state classes the Oris tool examples of application

... use state classes as a measure of probability over the set of runs

- tree of stochastic state classes
 - explicit representation for the measure of probability over sets of runs ¹²
 - discrete probability to reach a class
 - continuous probability measure over any subset of remaining times when the class is reached



- characterizes the process at the time when a class is entered
 - characterization w.r.t. absolute time when the class is reached obtained by supplementing classes with a global age variable ¹³

¹²M.Paolieri, A.Horváth, E.Vicario "Probabilistic Model Checking of Regenerative Concurrent Systems," accepted, IEEE Trans. on Software Engineering, Feb. 2016.

¹³A.Horváth, M.Paolieri, L.Ridi, E.Vicario, "Transient analysis of non-Markovian models using stochastic state classes," PEva, 2012.

the method of stochastic state classes the Oris tool examples of application

measures enabled by transient stochastic state classes

• probability that class *S* is reached within time *t*:

$$\pi_{\mathcal{S}} \cdot \int_{D \wedge -x_{age} \leq t} f_{\langle \tau_{age}, \underline{\tau} \rangle}(x_{age}, \underline{x}) dx_{age} d\underline{x}$$

probability that S is the last entered class at time t
 (S is reached within u ≤ t, the sojourn time is not lower than t − u)

$$\begin{aligned} \pi_{\mathcal{S}}(t) &= \pi_{\mathcal{S}} \cdot \int_{D(t)} f_{\langle \tau_{age}, \underline{\tau} \rangle}(x_{age}, \underline{x}) dx_{age} d\underline{x} \\ D(t) &= D \land (-x_{age} \leq t) \land (-x_{age} + \textit{Min}_n\{x_n\} \geq t) \end{aligned}$$



the method of stochastic state classes the Oris tool examples of application

transient analysis straight through the probability measure

- a straight approach to transient analysis:
 - · enumerate classes until the time horizon is overcome
 - not only for MRP, also for GSMP



- fairly general termination conditions
 - exact analysis terminates iff the non-deterministic SCG does not reach within time *T* any *possibly immediate* cycle
 - analysis with safe approximation ε > 0 terminates iff the non-deterministc SCG does not reach within time T any necessarily immediate cycle (time block)
- yet, the transient stochastic tree grows exponentially with the number of transition firings within the scope of transient analysis

combine stochastic state classes with Markov renewal theory

- restrain transient analysis within the first epoch use it to evaluate local and global kernels, and then resort to Markov Renewal Theory for MRPs
- derive kernels through measures on enumerated classes
 - local kernel: starting from *i*, at time *t* the marking is *j* and no regeneration has occurred

$$L_{ih}(t) := Prob(t_1 > t \land m(t) = h|m(t_0) = i \land t_0 = 0)$$

• global kernel: starting from *i*, the first regeneration is before *t* and leads to *j*

$$G_{ij}(t) := Prob(t \ge t_1 \land m(t_1) = j | m(t_0) = i \land t_0 = 0)$$

• get transient probabilities through generalized Markov renewal equations

$$\pi_{ii}(t) := Prob\{m(t) = l|m(0) = i\}$$

$$\pi_{ii}(t) = L_{ii}(t) + \sum_{k} \int_{x=0}^{t} \frac{dG_{ik}}{dx}(x)\pi_{ki}(t-x)dx$$

the method of stochastic state classes the Oris tool examples of application

analysis in the Oris tool

- full Java implementation in the Oris tool ¹⁴
 - rich extension of sTPN
 - approximation allowed
 - rewards
 - various analysis techniques
 - ... much more in the API
- underlying implementation also available, with many more functions
 - Sirio: symbolic calculus of PDF over DBM
 - PetriNetLib: syntax and semantics of Petri Nets, easily open to extensions
 - abstractEditor: a customizable framework for the production of graph-based formalisms



¹⁴ http://www.oris-tool.org/

the method of stochastic state classes the Oris tool examples of application

map of concepts: The Oris tool and the Sirio library



the method of stochastic state classes the Oris tool examples of application

unavailability and unreliability



O2 Configuration of engine X	
Configuration of Re	generative transient analysis
Analysis name:	unreliability and unavailability (100)
Time limit:	1000
Allowed error:	0
Discretization step:	0,5
	Extended regenerations Verbose
Stop condition:	
Rewards:	+Detected>0 Rej>0,1,0); If(Ok>0 && Rej>0,1,0)
	Cumulative rewards
	OK Annulla

- unreliability: Ko
- unavailability: Ko>0 || Detected>0 || Rej>0
- added unavailability: Ok>0 && Rej>0



the method of stochastic state classes the Oris tool examples of application

unavailability - cumulative





- unavailability: Ko>0 || Detected>0 || Rej>0
- added unavailability: Ok>0 && Rej>0



the method of stochastic state classes the Oris tool examples of application

unreliability - first passage time



Configuration of Regenerative transient analysis		
Analysis name:	first passage unreliability (100)	
Time limit	1000	
Allowed error:	0	
Discretization step:	0,5	
	Extended regenerations	
	Uerbose	
Stop condition:	Ko>0	
Rewards:	Ko	
	Cumulative rewards	
	OK Annulla	

unreliability: Ko>0



the method of stochastic state classes the Oris tool examples of application

unreliability - first passage time - 50



unreliability: Ko>0

Os Configuration or e	ngine	~
Configuration of Reg	enerative transient analysis	X
Analysis name:	unreliability - first passage time - 50	
Time limit:	250	
Allowed error:	0	
Discretization step:	0,1	
	Stended recenerations	
	U Verbene	
	verbose	
Stop condition:	K0>0	
Rewards:	Ko	
	Cumulative rewards	
	ок	Annulla



the method of stochastic state classes the Oris tool examples of application

unavailability - cumulative - 50



O2 Configuration of engine	
Configuration of Reg	enerative transient analysis
Analysis name:	unavailability - cumulative - 50
Time limit	250
Allowed error:	0
Discretization step:	0,1
	 Extended regenerations
	Urbose
Stop condition:	
Rewards:	Detected>0 Rej>0,1,0); If(Ok>0 && Rej>0,1,0)
	Cumulative rewards
	OK Annulla

- unavailability: Ko>0 || Detected>0 || Rej>0
- added unavailability: Ok>0 && Rej>0



the method of stochastic state classes the Oris tool examples of application

... some experiments of application

- dependability/performance evaluation of ...
 - performability evaluation for ERTMS/ETCS-level3
 - recoverability and serviceability in gas distribution networks
 - ... and water distribution networks
- on-line implementation as smart component of ...
 - Activity Recognition (AR) in Ambient Assisted Living (AAL)

performability evaluation for ERTMS/ETCS-level3

- impact of communication (un)availability in headway control for a chasing train in the RTCS level-3 signalling standard ¹⁵
 - trade off between headway distance (capacity) and breaking probability



• a transient problem, with multiple concurrent GEN durations

previous works on steady state, and under enabling restriction¹⁶

¹⁵M. Biagi, L. Carnevali, M. Paolieri, and E. Vicario, "Performability evaluation of the ERTMS/ETCS - Level 3", Transportation Research Part C: Emerging Technologies, Sept.2017.

¹⁶A.Zimmermann, G.Hommel, "Towards modeling and evaluation of ETCS realtime communication and operation," Journal of Systems and Software, 2005

the method of stochastic state classes the Oris tool examples of application

European Rail Traffic Management System (ERTMS)

- ERTMS: standard for train signalling and traffic management
- based on the European Train Control System (ETCS)
 - Automatic train protection system for continuous train supervision
 - A trackside equipment receives a periodic Position Report (PR) for each supervised train and sends back a Movement Authority (MA)
 - A train triggers an emergency brake if the allowed speed is exceeded



- ERTMS/ETCS Level 3 of operation
 - Moving-block signalling: trains check position and integrity autonomously
 - No train detection systems: installation/maintenance savings, capacity gains
 - Mobile communication is key: trade-off between capacity and false alarms



the method of stochastic state classes the Oris tool examples of application

first-passage time distribution to emergency brake due to GSM-R failures

- GSM-R failures due to burst noise, connection losses, handovers composed with a model of periodic transmission of PRs and MAs ¹⁷
 - Non-Markovian models specified through Stochastic Time Petri Nets (STPN)
 - Periodic handovers of a pair of chasing trains are dependent events
 - Stochastic parameters from Zimmermann et al (2003, 2005), and amendments in the evolution of the ERTMS/ETCS specification



¹⁷M. Biagi, L. Carnevali, M. Paolieri, and E. Vicario, "Performability evaluation of the ERTMS/ETCS - Level 3", Transportation Research Part C: Emerging Technologies, Sept.2017.

the method of stochastic state classes the Oris tool examples of application

combination of analytic evaluation and transient analysis

- Stochastic evaluation of the flat model would be practically not feasible
 - Transient analysis via the ORIS Tool (http://www.oris-tool.org) ¹⁸ would suffer the many concurrent timers with general (GEN) distribution
 - Approaches based on the approximation of GEN transitions ^{19 20 21}
 - Simulation would suffer rare events, different order of magnitude of durations
- GSM-R failures are due to independent phenomena
- GSM-R unavailability is evaluated separately for each failure type either analytically or through transient analysis via the ORIS Tool
 - Multiple losses due to burst noise can be regarded as independent events
 - Connection losses negligibly affect the GSM-R availability wrt burst noise
 - At most 2 out of 4 consecutive PRs and/or MAs can be lost due to handovers
- Evaluation within 2 hyper-periods yields an upper-bound on the first passage time distribution to an emergency brake in an unbounded interval

¹⁸A.Horváth, M.Paolieri, L.Ridi, E.Vicario, Transient analysis of non-Markovian models using stochastic state classes. Performance Evaluation, 2012.

¹⁹A.Horvath, A.Puliafito, M.Scarpa, M.Telek, Analysis and Evaluation of non-Markovian Stochastic Petri Nets. Int. Conf. on Computer Performance Evaluation, 2000.

²⁰F.Longo, M.Scarpa, Applying Symbolic Techniques to the Representation of Non-Markovian Models with Continuous PH Distributions. EPEW, 2009.

²¹C.Lindemann, A.Thümmler, Transient analysis of deterministic and stochastic Petri nets with concurrent deterministic transitions. Performance Evaluation, 1999

Upper-bound on first-passage time distribution to emergency brake due to GSM-R failures - 1/2

- Upper-bound on the first-passage probability that an emergency brake occurs within H hyper-periods, computed for different headway delays $T_{\rm h}$
 - The duration of a hyper-period is 84 $\textit{sec} \Rightarrow$ 45 hyper-periods $\sim 1\textit{hour}$

• The train speed is 300 Km/hour



the method of stochastic state classes the Oris tool examples of application

Upper-bound on first-passage time distribution to emergency brake due to GSM-R failures - 2/2

 Upper-bound on the first-passage probability that an emergency brake occurs within 45 hyper-periods (~ 1 *hour*) as a function of the headway distance s_h (expressed in *km*), computed for different values of speed v



the method of stochastic state classes the Oris tool examples of application

Recoverability and serviceability in gas distribution networks

 Gas distribution networks couple physical fluid-dynamic processes with cyber management procedures ²² ²³ ²⁴



 Goal: evaluate the low pressure risk in the transient phase after a repair, due to a contingency or a planned operation of pipe sectioning



²² M. Biagi, L. Carnevali, F.Tarani, E. Vicario, "Model-based quantitative evaluation of repair procedures in gas distribution networks", submitted to ACM Transactions on Cyber-Physical Systems.

²³ L. Carnevali, M. Paolieri, F. Tarani, E. Vicario, and K. Tadano, "Modeling and evaluation of maintenance procedures for gas distribution networks with time-dependent parameters", in Int. Workshop on Reliability and Security Aspects for Critical Infrastructure Protection (ReSA4CI), 2014.

²⁴ L. Carnevali, M. Paolieri, K. Tadano, and E. Vicario, "Towards the Quantitative Evaluation of Phased Maintenance Procedures Using Non-Markovian Regenerative Analysis", in European Performance Engineering Workshop (EPEW), 2013.

the method of stochastic state classes the Oris tool examples of application

Recoverability and serviceability in *water* distribution networks

- A more complex and different problem than what might appear, formulated with reference to the class of stochastic hybrid systems ²⁵
 - Water distribution networks feature a continuous and discrete dynamics (with the water level in tanks comprising a continuous element of memory)
 - Topology and operation mode can be changed at stochastic time points



Goal: evaluate the expected demand not served in the time after a repair



²⁵ L. Carnevali, F. Tarani, E. Vicario, "Performability evaluation of water distribution systems during maintenance procedures", IEEE Transactions on Systems, Man, and Cybernetics: Systems, accepted for publication.

the method of stochastic state classes the Oris tool examples of application

Activity Recognition (AR) in Ambient Assisted Living (AAL)

- A problem of diagnosis in a partially-observable system ^{26 27}
 - A stochastic model is rejuvenated by runtime observations
 - Transient probabilities computed on the model@runtime provide a likelihood for the diagnosis of the current state



- A kind of continuous-time extension of Hidden Markov Models (HMMs)
 - Exploiting the conditionment of the observation of times between events
 - Relevant only in non-Markovian systems

²⁶M. Biagi, L. Carnevali, M.Paolieri, F. Patara, E. Vicario, "A continuous-time model-based approach for activity recognition in pervasive environments", submitted to IEEE Transactions on Human-Machine Systems.

²⁷ L. Carnevali, C. Nugent, F. Patara, E.Vicario, "A continuous-time model-based approach to activity recognition for ambient assisted living", in International Conference on Quantitative Evaluation of SysTems (QEST), pp. 38-53, 2015.

... from diagnosis towards prediction and scheduling

- starting from each plausible current state, compute the distribution of the hitting time of some critical state
- schedule the time point of some typed action
 - in the AAL setting: schedule monitoring escalation or warnings
 - applicable to a variety of scenarios with a sensing and actuation infrastructure
- a tailored application giving value to effective evaluation of transient behavior

a few closing remarks:

- much more to be done in the solution of non-Markovian models ... and large potential of application of existing tools
- about verification vs evaluation and qualitative (non-deterministic) vs quantitative (stochstic)
- about verification of Real Time constraints on Markovian models
 - systems with real time requirement natively include firm timing mechanisms (e.g. timeouts, watchdogs, periodic releases, bounded execution times)
 - which break the assumptions of memoryless and unbounded behavior of EXP variables,
 - and require representation of generally distributed (GEN) durations
 - not always enabling clean mathematics but relevant for engineering
- about quantitative evaluation and model-based approaches in the age of big data and machine learning