

Formal languages for stochastic modelling

Jane Hillston

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Outline

- 1** Introduction: Performance Modelling and Process Algebras
 - Performance Modelling
 - Stochastic Process Algebra

- 2** Tackling State Space Explosion
 - Lumpability and Bisimulation
 - Fluid Approximation

- 3** Beyond Performance Modelling

The PEPA project

- The PEPA project started in Edinburgh in 1991.
- It was motivated by problems encountered when carrying out performance analysis of large computer and communication systems, based on numerical analysis of Markov chains.
- Process algebras offered a compositional description technique supported by apparatus for formal reasoning.
- Performance Evaluation Process Algebra (PEPA) sought to address these problems by the introduction of a suitable process algebra.
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Performance Modelling

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There are often conflicting interests at play:

- Users typically want to optimise external measurements of the dynamics such as response time (as small as possible), throughput (as high as possible) or blocking probability (preferably zero);
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Does performance matter...?

There is sometimes a perception in software development that **performance** does not matter much, or that it is easily fixed later by buying a faster machine.

On the contrary — studies have shown that **response time** is a key feature in **user satisfaction** and **trust** in systems.

In a study by Amazon they artificially delayed page loading times in increments of 100 milliseconds. Even such very small delays were observed to result in substantial and costly drops in revenue.

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Continuous Time Markov Chains

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This dates back to Erlang's Loss Formula for the performance of telephone exchanges in the early 20th century.

In the 1960s and 1970s queueing networks were used extensively, but the advent of distributed systems in the 1980s meant that many systems no longer fit the assumptions of queueing networks.

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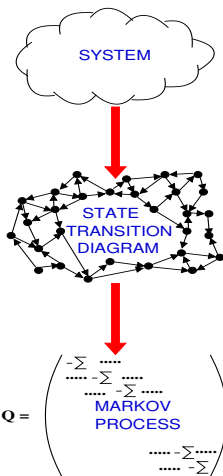
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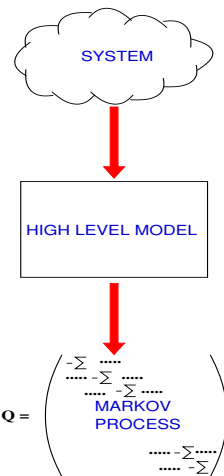
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Performance Modelling using CTMC

Model Construction

- describing the system using a high level modelling formalism
- generating the underlying CTMC



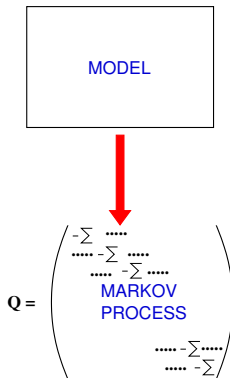
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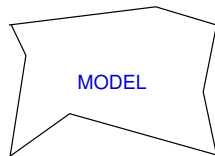
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MARKOV
PROCESS

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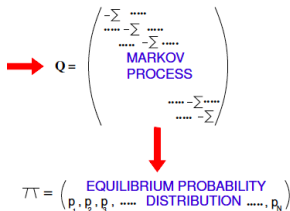
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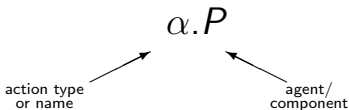
Model Solution

- solving the CTMC to find steady state or transient probability distribution
- deriving performance measures



Process Algebra

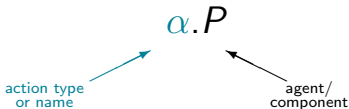
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- The structured operational (interleaving) semantics of the language is used to generate a **labelled transition system**.

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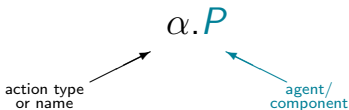
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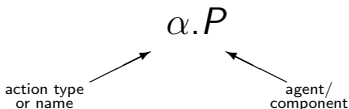
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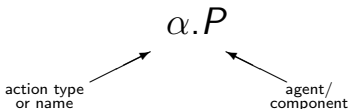
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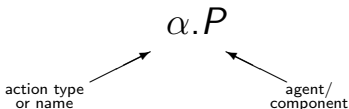


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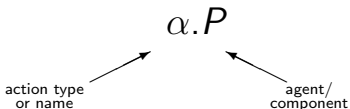


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Process algebra model $\xrightarrow{\text{SOS rules}}$ Labelled transition system

Process algebra operators

Process algebras generally have a number of different operators for combining actions and components, typically including:

- Prefix $.$ – designated first action;
- Choice $+$ – selection between alternative components;
- Parallel composition \parallel – components working concurrently;

These operators have rules associated with them such as

$$P \parallel (Q \parallel R) = (P \parallel Q) \parallel R$$

and

$$P + P = P$$

Bisimulation and congruence

Process algebras are usually equipped with an equivalence relation, termed a **bisimulation**, meaning that one component is equivalent to another if it can copy or simulate any action of the other component and vice versa.

Languages are designed so that these relations are designed so that these equivalence relations are **congruences** with respect to the operators of the language.

For example, if $P \sim Q$ then

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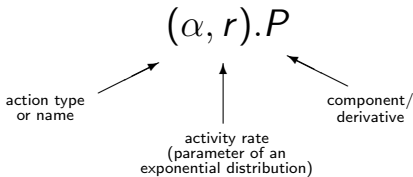
Stochastic process algebras

Stochastic process algebra

Process algebras where models are decorated with quantitative information used to generate a stochastic process are **stochastic process algebras (SPA)**.

Stochastic Process Algebra

- Models are constructed from **components** which engage in **activities**.

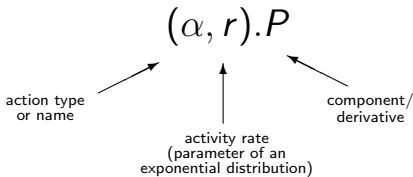


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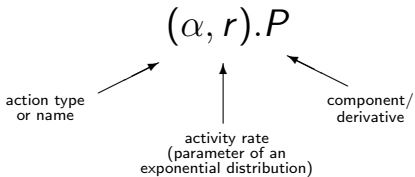


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Performance Evaluation Process Algebra

PEPA **components** perform **activities** either independently or in **co-operation** with other components.

$(\alpha, r).P$	Prefix
$P_1 + P_2$	Choice
$P_1 \bowtie_L P_2$	Co-operation
P/L	Hiding
X	Variable

$P_1 \parallel P_2$ is a derived form for $P_1 \bowtie_{\emptyset} P_2$.

When working with large numbers of entities, we write $P[n]$ to denote an array of n copies of P executing in parallel.

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A simple example: processors and resources

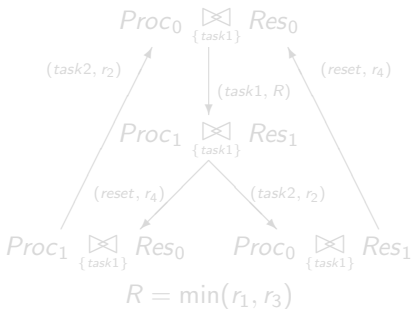
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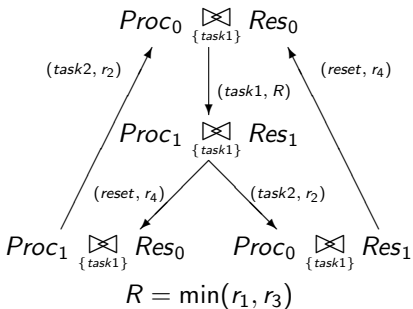
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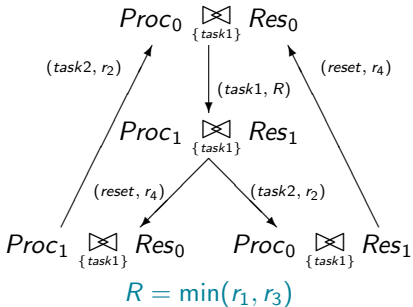
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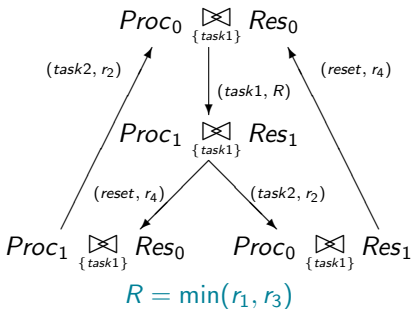
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- **High level description** of the system eases the task of model construction.
- **Formal language** allows for unambiguous interpretation and automatic translation into the underlying mathematical structure.
- **Properties of that mathematical structure** may be deduced by the construction at the process algebra level.
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For example,

- The correspondence between the congruence, **Markovian bisimulation**, in the process algebra and the **lumpability** condition in the CTMC, allows exact model reduction to be carried out **compositionally**.
- Characterisation of **product form** structure at the process algebra level allows **decomposed model solution** based on the process algebra structure of the model.
- **Stochastic model checking** based on the Continuous Stochastic Logic (CSL) family of temporal logics allows automatic evaluation of **quantified properties** of the behaviour of the system.

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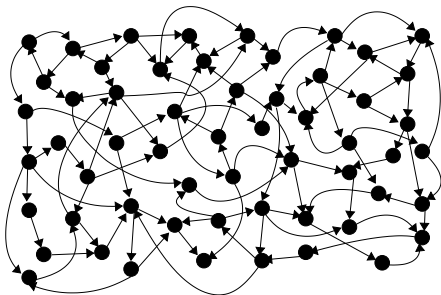
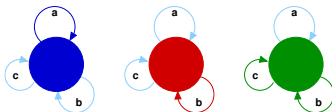
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Outline

- 1 Introduction: Performance Modelling and Process Algebras
 - Performance Modelling
 - Stochastic Process Algebra
- 2 Tackling State Space Explosion
 - Lumpability and Bisimulation
 - Fluid Approximation
- 3 Beyond Performance Modelling

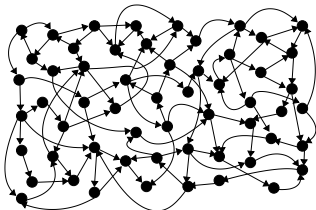
Deriving performance measures

Under the SOS semantics a SPA model is mapped to a CTMC with global states determined by the local states of all the participating components.



Deriving performance measures

When the size of the state space is not too large they are amenable to **numerical solution** (linear algebra) to determine a **steady state** or **transient probability distribution**.

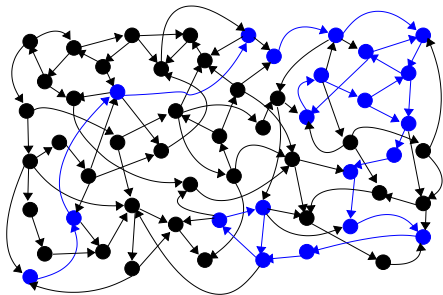


$$Q = \begin{pmatrix} q_{1,1} & q_{1,2} & \cdots & q_{1,N} \\ q_{2,1} & q_{2,2} & \cdots & q_{2,N} \\ \vdots & \vdots & & \vdots \\ q_{N,1} & q_{N,2} & \cdots & q_{N,N} \end{pmatrix}$$

$$\pi(t) = (\pi_1(t), \pi_2(t), \dots, \pi_N(t))$$

Deriving performance measures

Alternatively they may be studied using **stochastic simulation**. Each run generates a single trajectory through the state space. Many runs are needed in order to obtain average behaviours.



State space explosion

As the size of the state space becomes large it becomes infeasible to carry out numerical solution and extremely time-consuming to conduct stochastic simulation.

Model Manipulation

Model simplification: use a **model-model** equivalence to substitute one model by another which is more attractive from a solution point of view, e.g. smaller state space, special class of model, etc.

Model aggregation: use a **state-state** equivalence to establish a partition of the state space of a model, and replace each set of states by one **macro-state**, i.e. take a different stochastic representation of the same model.

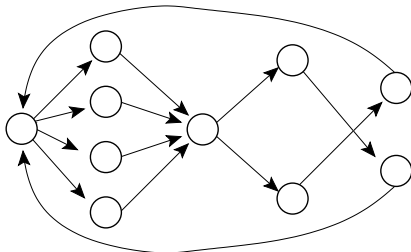
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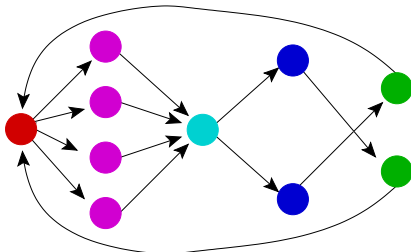
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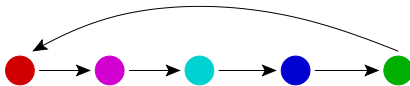
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Lumpability

- In the early 1960's Kemeny and Snell established the conditions under which it was possible to aggregate a Markov chain and still have a Markov chain afterwards.
- In particular these conditions were characterised by conditions on the rates.
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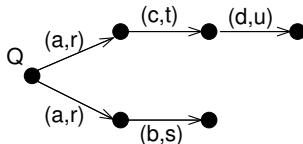
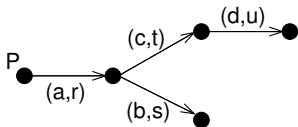
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In process algebra equivalence relations are defined based on the notion of [observability](#):

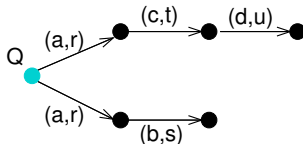
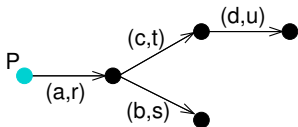
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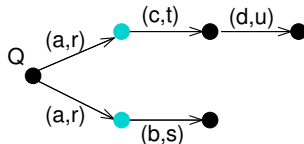
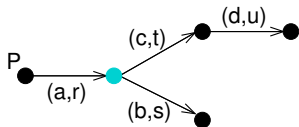
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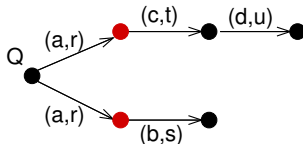
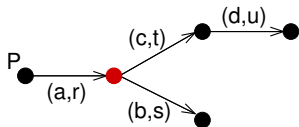
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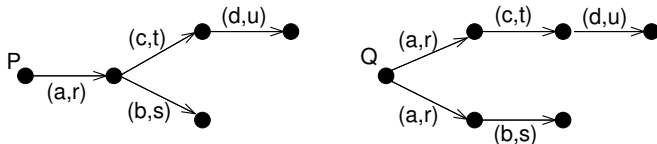
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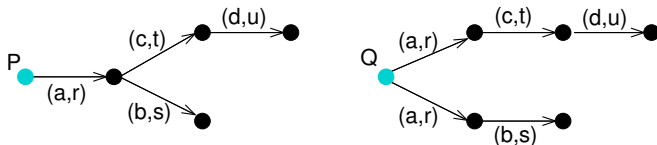
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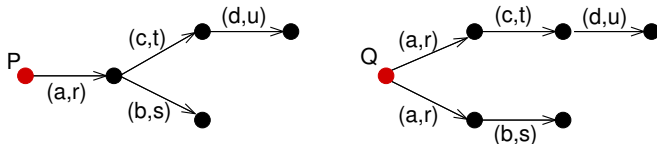
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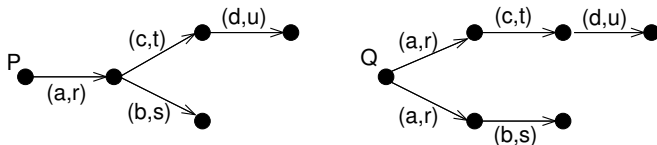
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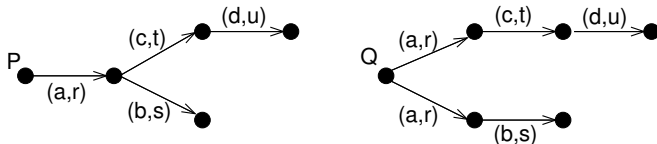


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The formal definition means this can be applied **automatically** and **compositionally**.

State space explosion

As the size of the state space becomes large it becomes infeasible to carry out numerical solution and extremely time-consuming to conduct stochastic simulation.

In these cases we would like to take advantage of the **mean field** or **fluid approximation** techniques.

Use **continuous state variables** to approximate the discrete state space and **ordinary differential equations** to represent the evolution of those variables over time.

Appropriate for models in which there are large numbers of components of the same type, i.e. models of populations and situations of collective dynamics.

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Fluid approximation theorem

Hypothesis

- $\bar{\mathbf{X}}^{(N)}(t)$: a sequence of normalized population CTMC, residing in $E \subset \mathbb{R}^n$
- $\exists \mathbf{x}_0 \in S$ such that $\bar{\mathbf{X}}^{(N)}(0) \rightarrow \mathbf{x}_0$ in probability (initial conditions)
- $\mathbf{x}(t)$: solution of $\frac{d\mathbf{x}}{dt} = F(\mathbf{x})$, $\mathbf{x}(0) = \mathbf{x}_0$, residing in E .

(Density dependent CTMCs are a special case.)

Theorem

For any finite time horizon $T < \infty$, it holds that:

$$\mathbb{P}\left(\sup_{0 \leq t \leq T} \|\bar{\mathbf{X}}^{(N)}(t) - \mathbf{x}(t)\| > \varepsilon\right) \rightarrow 0.$$

Simple example revisited

$$Proc_0 \stackrel{def}{=} (task1, r_1).Proc_1$$

$$Proc_1 \stackrel{def}{=} (task2, r_2).Proc_0$$

$$Res_0 \stackrel{def}{=} (task1, r_1).Res_1$$

$$Res_1 \stackrel{def}{=} (reset, r_4).Res_0$$

$$Proc_0[N_P] \bowtie_{\{task1\}} Res_0[N_R]$$

Simple example revisited

CTMC interpretation

Processors (N_P)	Resources (N_R)	States ($2^{N_P+N_R}$)
1	1	4
2	1	8
2	2	16
3	2	32
3	3	64
4	3	128
4	4	256
5	4	512
5	5	1024
6	5	2048
6	6	4096
7	6	8192
7	7	16384
8	7	32768
8	8	65536
9	8	131072
9	9	262144
10	9	524288
10	10	1048576

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- *task1* decreases $Proc_0$ and Res_0
- *task1* increases $Proc_1$ and Res_1
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$$\frac{dx_1}{dt} = -\min(r_1 x_1, r_3 x_3) + r_2 x_2$$

$x_1 = \text{no. of } Proc_1$

- *task1* decreases $Proc_0$
- *task1* is performed by $Proc_0$ and Res_0
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$$\frac{dx_2}{dt} = \min(r_1 x_1, r_3 x_3) - r_2 x_2$$

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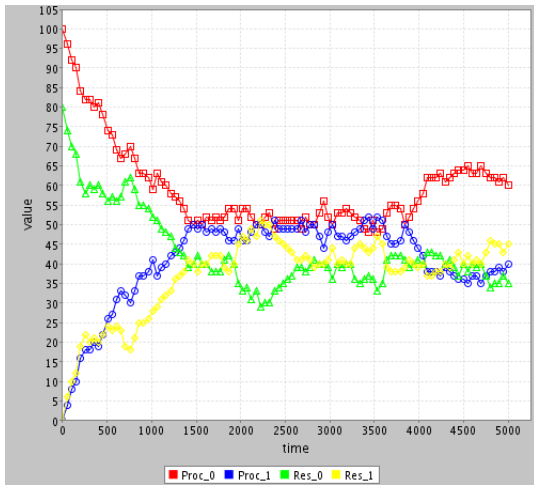
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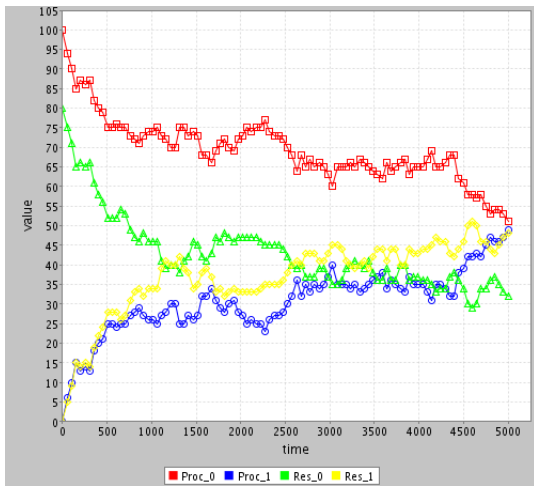
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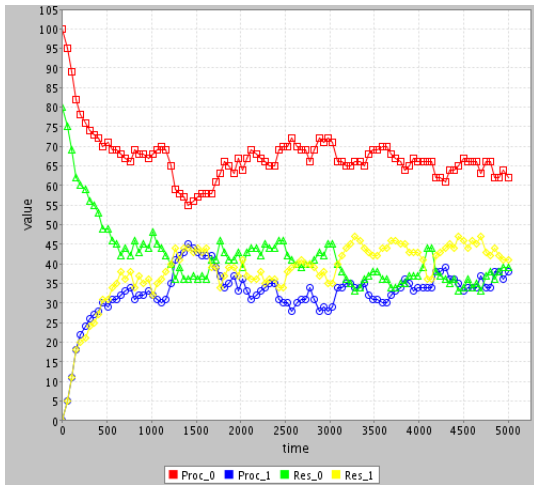
100 processors and 80 resources (simulation run A)



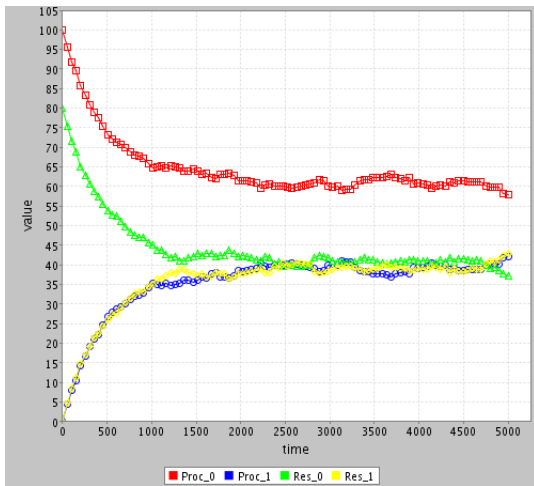
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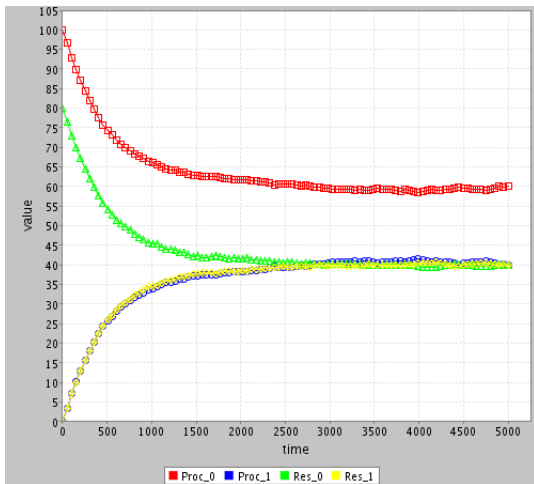
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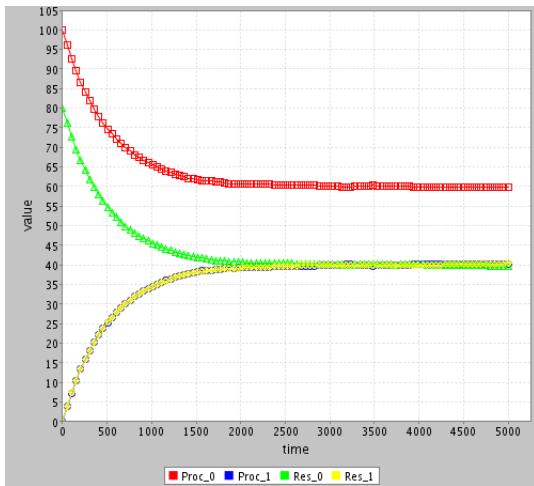
100 processors and 80 resources (average of 10 runs)



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100 processors and 80 resources (average of 1000 runs)



Deriving a Fluid Approximation of a PEPA model

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The existing (CTMC) SOS semantics is not suitable for this purpose because it constructs the **state space** of the CTMC **explicitly**.



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Fluid Structured Operational Semantics

In order to get to the implicit representation of the CTMC we need to:

- 1 **Context Reduction:** Remove excess components to find the abstract state representation ξ .
- 2 **Jump Multiset:** Collect the transitions α of the reduced context in terms of update vectors l .
- 3 **Generating Functions:** Calculate the rate of the transitions in terms of an arbitrary state of the CTMC, $f(\xi, l, \alpha)$.

Once this is done we can extract the vector field $F_{\mathcal{M}}(x)$ from the jump multiset.

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Rate properties of PEPA models

Density dependence of parametric transition rates

The transition rates scale in the same way as the population, i.e. if $P \xrightarrow{(\alpha, r(\xi))} Q$ then, for any $n \in \mathbb{N}$, $r(\xi) = n \cdot r(\xi/n)$

Generating functions give rise to density dependent rates

Let \mathcal{M} be a PEPA model with generating functions $f(\xi, l, \alpha)$. Then the corresponding sequence of CTMCs will be density dependent.

Lipschitz continuity of parametric apparent rates

Let $r_\alpha^*(P, \xi)$ be the parametric apparent rate of action type α in process P . There exists a constant $L \in \mathbb{R}$ such that for all $x, y \in \mathbb{R}^d, x \neq y$,

$$\frac{\|r_\alpha^*(P, x) - r_\alpha^*(P, y)\|}{\|x - y\|} \leq L$$

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Kurtz's Theorem

Kurtz's Theorem for PEPA

Let $x(t), 0 \leq t \leq T$ satisfy the initial value problem
 $\frac{dx}{dt} = F(x(t)), x(0) = \delta$, specified from a PEPA model.

Let $\{X_n(t)\}$ be a family of CTMCs with parameter $n \in \mathbb{N}$
 generated as explained and let $X_n(0) = n \cdot \delta$. Then,

$$\forall \varepsilon > 0 \lim_{n \rightarrow \infty} \mathbb{P} \left(\sup_{t \leq T} \|X_n(t)/n - x(t)\| > \varepsilon \right) = 0.$$

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Outline

- 1 Introduction: Performance Modelling and Process Algebras
 - Performance Modelling
 - Stochastic Process Algebra
- 2 Tackling State Space Explosion
 - Lumpability and Bisimulation
 - Fluid Approximation
- 3 Beyond Performance Modelling

Stochastic process algebras

Over the last two decades stochastic process algebras (mostly with Markovian semantics) have been applied to a wide range of application domains.

In some case there have been new languages developed to support particular features of the application domain. These have included stochastic process algebras for modelling hybrid systems, spatial temporal systems and ecological processes.

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Molecular processes as concurrent computations

Concurrency	Molecular Biology	Metabolism	Signal Transduction
Concurrent computational processes	Molecules	Enzymes and metabolites	Interacting proteins
Synchronous communication	Molecular interaction	Binding and catalysis	Binding and catalysis
Transition or mobility	Biochemical modification or relocation	Metabolite synthesis	Protein binding, modification or sequestration

A. Regev and E. Shapiro *Cells as computation*, Nature 419, 2002.

Bio-PEPA modelling

- The **state of the system** at any time consists of the **local states** of each of its sequential/species components.
- The local states of components are **quantitative** rather than functional, i.e. biological changes to species are represented as distinct components.
- A component varying its state corresponds to it varying its **amount**.
- This is captured by an integer parameter associated with the species and the effect of a reaction is to vary that parameter by a number corresponding to the **stoichiometry** of this species in the reaction.

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The abstraction

- Each species i is described by a species component C_i
- Each reaction j is associated with an action type α_j and its dynamics is described by a specific function f_{α_j}

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The syntax

Sequential component (species component)

$$S ::= (\alpha, \kappa) \text{ op } S \mid S + S \mid C \quad \text{where op} = \downarrow \mid \uparrow \mid \oplus \mid \ominus \mid \odot$$

Model component

$$P ::= P \underset{\mathcal{L}}{\bowtie} P \mid S(I)$$

Each action α_j is associated with a rate f_{α_j}

The list \mathcal{N} contains the numbers of levels/maximum concentrations

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The semantics

The semantics is defined by two transition relations:

- First, a **capability relation** — is a transition possible?
- Second, a **stochastic relation** — gives rate of a transition, derived from the parameters of the model.

The labelled transition system generated by the stochastic relation formally defines the **underlying CTMC**.

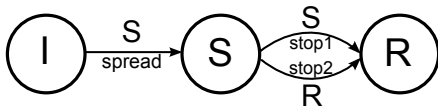
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Example — in Bio-PEPA



```
k_s = 0.5;
```

```
k_r = 0.1;
```

```
kineticLawOf spread : k_s * I * S;
```

```
kineticLawOf stop1 : k_r * S * S;
```

```
kineticLawOf stop2 : k_r * S * R;
```

```
I = (spread,1) ↓ ;
```

```
S = (spread,1) ↑ + (stop1,1) ↓ + (stop2,1) ↓ ;
```

```
R = (stop1,1) ↑ + (stop2,1) ↑ ;
```

```
I[10] ⊗ S[5] ⊗ R[0]
```


Conclusions

- **Stochastic process algebras** provide high-level description languages which can ease the task of model construction for large CTMC models.
- The **formal** nature of the language allows for unambiguous interpretation and automatic CTMC generation.
- Properties of the underlying mathematical structure can be detected at the **syntax level** and **proof obligations** can be carried out once and for all in the semantics of the language.
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Thank you