## Population Modelling

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Modelling collective adaptive systems quantitatively


## Motivation

- application area: collective adaptive systems (CAS)
- smart transport - buses, bike sharing
- smart grid - electricty generation and consumption
- we want model to quantitative behaviour of these systems and be able to characterise their performance
- we take a population-based approach where there are a large number of identical processes
- many processes leads to well-known problem of state space explosion
- mitigate this problem with approximation techniques
- focus in this talk on a general process algebra approach to modelling populations, moving beyond application to biology


## Quantitative modelling



## Modelling with PEPA

- PEPA [Hillston, 1996]
- two-level grammar, constant definition, $C \stackrel{\text { def }}{=} S$

$$
\begin{aligned}
& S::=(a, r) \cdot S \mid S+S \\
& P::=S \mid P \nsim P
\end{aligned}
$$

multi-way synchronisation (CSP-style)

- operational semantics define labelled multi-transition system
- $P_{1} \xrightarrow{(a, r)} P_{2}$
- labelled continuous-time Markov chain (CTMC)
- what happens when there are many sequential processes?
- assume $n$ sequential constants: $C_{1}, \ldots, C_{n}$
- each constant has a maximum of $m$ states: $S_{1,1}, \ldots, S_{1, m}$
- CTMC has a maximum of $n^{m}$ states


## Modelling with PEPA

## Quotienting by bisimilarity

- what if many of the sequential processes are the same?
- consider the states
- $\left(S_{1,1}, S_{1,1}, S_{1,2}, S_{4, j_{4}}, \ldots, S_{n, j_{n}}\right)$
- $\left(S_{1,2}, S_{1,1}, S_{1,1}, S_{4, j_{4}}, \ldots, S_{n, j_{n}}\right)$
- both have the same numbers of $S_{1,1}$ and $S_{1,2}$
- numeric vector representation
- $\left(\# S_{1,1}, \# S_{1,2} \ldots \# S_{1, m} ; \ldots \ldots ; \# S_{n^{\prime}, 1}, \# S_{n^{\prime}, 2}, \ldots \# S_{n^{\prime}, m}\right)$
- $n^{\prime}$ is number of different types of sequential constants
- introduces functional rates
- stochastically bisimilar
- smaller state space?
- $p$ is the maximum count of any state $S_{i, j}$
- CTMC has a maximum of $\left(n^{\prime} \times m\right)^{p+1}$ states


## Using numeric vector representation

| Modelling | P | $C_{1}\left[x_{1}\right] \underset{L}{\otimes} \ldots \underbrace{}_{L} C_{n^{\prime}}\left[x_{n^{\prime}}\right]$ |
| :---: | :---: | :---: |
| Language | \| |  |
| semantic mapping | CTMC $\downarrow$ |  |
| Mathematical | $\mathbf{S}_{\text {CTMC }}$ | $\left(\# S_{1,1}, \ldots ; \ldots \# S_{n^{\prime}, m}\right)$ |
| Representation | $\square$ |  |
| analysis technique | steady state |  |
| Result | $\mathbf{R}_{\text {CTMC }}$ | $\left(p_{1}, \ldots \ldots, p_{\left(n^{\prime} \times m\right)^{p+1}}\right)$ |
|  |  | OPCT, June $2014 \quad 8 / 29$ |

## Fluid/mean-field approximation

- numeric vector representation can still result in a large number of states so use a fluid approximation [Hillston, 2005]
- treat subpopulation counts as real rather than integral and express change over time as ordinary differential equations (ODEs) giving one equation for each sequential state: $n^{\prime} \times m$
- seldom obtain ODEs with analytical solutions but numerical ODE solution is generally fast
- ODE behaviour can approximate CTMC behaviour well if sufficient numbers (together with some other conditions as shown by Kurtz)


## Fluid/mean-field approximation

## Languages for modelling populations

- extensions to PEPA: multiple states per entity
- Grouped PEPA [Hayden, Stefanek and Bradley, 2012]
- Fluid process algebra [Tschaikowski and Tribastone, 2014]
- biological: single state and count per species
- Bio-PEPA [Ciocchetta and Hillston, 2009]
- Bio-PEPA with compartments [Ciocchetta and Guerriero, 2009]
- epidemiological: single state and count per subpopulation
- variant of Bio-PEPA with locations
[Ciocchetta and Hillston, 2010]


## A stochastic population process algebra

- stochastic and deterministic semantics
- aim to be general but elementary
- each entity has a single state and a count
- is there a suitable equivalence?
- compression bisimulation [Galpin and Hillston, 2011]
- start more concretely and then consider more generality
- syntax from epidemiological modelling but different semantics


## A stochastic population process algebra

- subpopulation description

$$
C \stackrel{\text { def }}{=}\left(\beta_{1},\left(\kappa_{1}, \lambda_{1}\right)\right) \odot C+\ldots+\left(\beta_{m_{C}},\left(\kappa_{m_{C}}, \lambda_{m_{c}}\right)\right) \odot C
$$

- actions: $\beta_{i}$ are distinct
- in and out stoichiometries: $\kappa_{i}, \lambda_{i} \in \mathbb{N}$
- composition of subpopulations

$$
P \stackrel{\text { def }}{=} C_{1}\left(n_{1,0}\right) \underset{*}{\nsim} \ldots \underset{*}{\circledast} C_{p}\left(n_{p, 0}\right)
$$

- subpopulations: $C_{j}$ are distinct,
- initial quantities: $n_{j, 0} \in \mathbb{N}$
- minimum and maximum size: $M_{C}$ and $N_{C}$ for each $C$
- range of a subpopulation is $N_{C}-M_{C}+1$
- use $C^{(n)}$ to distinguish subpopulations with different ranges
- $P^{(n)}$ defines a composition whose minimum range is $n$


## Operational semantics

$$
\begin{gathered}
C \stackrel{\text { def }}{=} \sum_{k=1}^{n_{C}}\left(\beta_{k},\left(\kappa_{k}, \lambda_{k}\right)\right) \odot C \\
\alpha \in\left\{\beta_{1}, \ldots, \beta_{n_{C}}\right\} \\
\kappa_{k} \leq n \leq N_{C}-\lambda_{k}
\end{gathered}
$$

## Operational semantics (continued)

$$
\begin{aligned}
& \frac{P \xrightarrow{\alpha, W}{ }_{c} P^{\prime}}{P \otimes Q \xrightarrow{\alpha, W}{ }_{c} P^{\prime} \otimes Q} \quad Q \xrightarrow{\alpha, W^{\prime}}{ }_{c} \\
& \frac{Q \xrightarrow{\alpha, W} c Q^{\prime}}{P \bowtie Q \xrightarrow{\alpha, W}{ }_{c} P^{\prime} \bowtie Q} \quad P \xrightarrow{\alpha, W^{\prime}} c \\
& \xrightarrow{P^{\alpha, W_{1}}}{ }_{c} P^{\prime} \quad Q \xrightarrow{\alpha, W_{2}}{ }_{c} Q^{\prime} \\
& P \bowtie \otimes_{*}^{\otimes} Q \xrightarrow{\alpha, W_{1} \cup W_{2}}{ }_{c} P^{\prime} \otimes Q^{\prime}
\end{aligned}
$$

## Operational semantics (continued)

$$
\frac{P \xrightarrow[c]{\alpha, W}_{c} P^{\prime}}{P{\xrightarrow{\alpha, f_{\alpha}(W)}}_{s} P^{\prime}}
$$

- $f_{\alpha}:(\mathcal{C} \rightarrow \mathbb{N}) \rightarrow \mathbb{R}_{\geq 0}$ where $\mathcal{C}$ is the set of subpopulations
- $f_{\alpha}$ may make reference to $M_{C}$ and $N_{C}$
- Markov chain semantics are given by $\xrightarrow{\alpha, r}{ }_{s}$
- ODE semantics can be derived from $C_{1}\left(n_{1,0}\right) \nVdash_{*} \ldots C_{p}\left(n_{p, 0}\right)$
- hybrid semantics by mapping to stochastic HYPE [Galpin 2014]
- dynamic switching between stochastic and deterministic semantics for each action depending on subpopulation size or rate


## Example

$$
\begin{array}{ll}
A \stackrel{\text { def }}{=}\left(\alpha_{1},(1,0)\right) \odot A+\left(\alpha_{2},(0,1)\right) \odot A+\left(\alpha_{3},(2,0)\right) \odot A \\
B & \stackrel{\text { def }}{=} \\
C \stackrel{\text { def }}{=}\left(\alpha_{1},(0,1)\right) \odot C+\left(\alpha_{2},(1,0)\right) \odot C &
\end{array}
$$

## Example

$$
\begin{aligned}
& A \stackrel{\text { def }}{=}\left(\alpha_{1},(1,0)\right) \odot A+\left(\alpha_{2},(0,1)\right) \odot \boldsymbol{A}+\left(\alpha_{3},(2,0)\right) \odot \boldsymbol{A} \\
& B \stackrel{\text { def }}{=} \\
& C \quad\left(\alpha_{3},(0,1)\right) \odot B \\
& C
\end{aligned}
$$

## Example

$$
\begin{array}{ll}
A \stackrel{\text { def }}{=}\left(\alpha_{1},(1,0)\right) \odot A+\left(\alpha_{2},(0,1)\right) \odot A+\left(\alpha_{3},(2,0)\right) \odot A \\
B \stackrel{\text { def }}{=} & \left(\alpha_{3},(0,1)\right) \odot B \\
C & \stackrel{\text { def }}{=}\left(\alpha_{1},(0,1)\right) \odot C+\left(\alpha_{2},(1,0)\right) \odot C
\end{array}
$$

## Example

$$
\begin{array}{ll}
A \stackrel{\text { def }}{=}\left(\alpha_{1},(1,0)\right) \odot A+\left(\alpha_{2},(0,1)\right) \odot A+\left(\alpha_{3},(2,0)\right) \odot A \\
B & \stackrel{\text { def }}{=} \\
C \stackrel{\text { def }}{=}\left(\alpha_{3},(0,1)\right) \odot B \\
&
\end{array}
$$

## Example

$A \stackrel{\text { def }}{=}\left(\alpha_{1},(1,0)\right) \odot A+\left(\alpha_{2},(0,1)\right) \odot A+\left(\alpha_{3},(2,0)\right) \odot A$
$B \stackrel{\text { def }}{=}$
$\left(\alpha_{3},(0,1)\right) \odot B$
$C \stackrel{\text { def }}{=}\left(\alpha_{1},(0,1)\right) \odot C+\left(\alpha_{2},(1,0)\right) \odot C$

- consider $A(5) \bowtie B(0) \nVdash_{*} C(0)$ and $A(7) \bowtie B(0) \bowtie C(0)$
- express as labelled transition systems in numerical vector representation $\left(n_{A}, n_{B}, n_{C}\right)$


## Example (continued)

$$
\begin{aligned}
& (5,0,0) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(4,0,1) \underset{\alpha_{3}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(3,0,2) \underset{\alpha_{3}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(2,0,3) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,0,4) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,0,5) \\
& (3,1,0) \underset{\alpha_{2}}{\rightleftarrows}(2,1,1) \underset{\alpha_{3}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,1,2) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,1,3) \\
& \alpha_{3} \downarrow \quad{ }_{\alpha_{1}}^{\alpha_{2}} \alpha_{3} \downarrow \\
& (1,2,0) \underset{\alpha_{2}}{\rightleftarrows}(0,2,1)
\end{aligned}
$$

## Example (continued)

$$
\begin{aligned}
& (5,0,0) \underset{\alpha_{3} \downarrow}{\stackrel{\alpha_{1}}{\rightleftarrows}}(4,0,1) \underset{\alpha_{1}}{\stackrel{\alpha_{3}}{\rightleftarrows} \downarrow} \underset{\alpha_{1}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(3,0,2) \underset{\alpha_{1}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(2,0,3) \underset{\alpha_{1}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,0,4) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,0,5) \\
& (3,1,0) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(2,1,1) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,1,2) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,1,3) \\
& \alpha_{3} \downarrow \quad{ }_{\alpha_{1}}^{\alpha_{2}} \alpha_{3} \downarrow \\
& (1,2,0) \underset{\alpha_{2}}{\rightleftarrows}(0,2,1)
\end{aligned}
$$

$$
\begin{aligned}
& \alpha_{3} \downarrow \quad{ }_{\alpha_{2}}^{\alpha_{1}} \alpha_{3} \downarrow \quad{ }_{\alpha_{2}}^{\alpha_{1}} \alpha_{3} \downarrow \quad{ }_{\alpha_{2}}^{\alpha_{1}} \alpha_{3} \downarrow \quad{ }_{\alpha_{1}}^{\alpha_{2}} \alpha_{3} \downarrow \quad{ }_{\alpha_{1}}^{\alpha_{2}} \alpha_{3} \downarrow \\
& (5,1,0) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(4,1,1) \underset{\alpha_{3} \downarrow}{\stackrel{\alpha_{1}}{\rightleftarrows}}(3,1,2) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(2,1,3) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,1,4) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,1,5) \\
& \begin{array}{l}
\alpha_{3} \downarrow \\
(3,2,0) \\
\alpha_{3} \downarrow \\
\alpha_{1} \\
\alpha_{1} \\
\alpha_{1} \downarrow \\
\alpha_{3} \downarrow \\
\left.\alpha_{3} \downarrow, 2,1\right)
\end{array} \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,2,2) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,2,3) \\
& (1,3,0) \underset{\alpha_{2}}{\stackrel{\rightharpoonup}{\rightleftarrows}}(0,3,1)
\end{aligned}
$$

## Example (continued)

$$
\begin{aligned}
& (5,0,0) \underset{\alpha_{3} \downarrow}{\stackrel{\alpha_{1}}{\rightleftarrows}}(4,0,1) \underset{\alpha_{1}}{\stackrel{\alpha_{1}}{\rightleftarrows}} \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(3,0,2) \underset{\alpha_{1}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(2,0,3) \underset{\alpha_{1}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,0,4) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,0,5) \\
& (3,1,0) \underset{\alpha_{3} \downarrow}{\stackrel{\rightharpoonup}{\alpha_{2}}}(2,1,1) \underset{\alpha_{3}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,1,2) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,1,3) \\
& \begin{array}{l}
\alpha_{3} \downarrow \stackrel{\alpha_{2}}{\alpha_{1}} \alpha_{3} \downarrow \\
(1,2,0) \underset{\alpha_{2}}{\rightleftarrows}(0,2,1)
\end{array}
\end{aligned}
$$

what is the equivalence that will identify these two models?

$$
\begin{aligned}
& (7,0,0) \underset{\alpha_{3} \downarrow}{\stackrel{\alpha_{1}}{\rightleftarrows}}(6,0,1) \underset{\alpha_{3} \downarrow}{\stackrel{\alpha_{1}}{\rightleftarrows}}(5,0,2) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(4,0,3) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(3,0,4) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(2,0,5) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,0,6) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,0,7)
\end{aligned}
$$

$$
\begin{aligned}
& (3,2,0) \underset{\alpha_{2}}{\rightleftarrows}(2,2,1) \underset{\alpha_{3}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,2,2) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,2,3) \\
& \alpha_{3} \downarrow \quad{ }_{\alpha_{1}}^{\alpha_{2}} \alpha_{3} \downarrow \\
& (1,3,0) \underset{\alpha_{2}}{\stackrel{1}{\rightleftarrows}}(0,3,1)
\end{aligned}
$$

## Single subpopulation

$$
\text { - } B \stackrel{\text { def }}{=}(\alpha,(3,0)) \odot B+(\beta,(0,4)) \odot B+(\gamma,(0,1)) \odot B
$$



## Single subpopulation

$$
B \stackrel{\text { def }}{=}(\alpha,(3,0)) \odot B+(\beta,(0,4)) \odot B+(\gamma,(0,1)) \odot B
$$

$B^{(16)}$


## Single subpopulation

- $B \stackrel{\text { def }}{=}(\alpha,(3,0)) \odot B+(\beta,(0,4)) \odot B+(\gamma,(0,1)) \odot B$
$B^{(16)} \underset{1}{1}$



## Single subpopulation



## Single subpopulation



## Single subpopulation



## Single subpopulation



## Single subpopulation



## Single subpopulation



## Compression bisimilarity

- $(P, Q) \in \mathcal{H}$ if they have same actions,
- define labelled transition system over equivalence classes of $\mathcal{H}$

$$
[P] \stackrel{\alpha}{\longleftrightarrow}[Q] \text { if } P \xrightarrow{(\alpha, v)} c Q
$$

- compression bisimilarity, $P \bumpeq Q$ if $[P] \sim[Q]$, namely whenever

1. $[P] \stackrel{\alpha}{\hookrightarrow}\left[P^{\prime}\right]$, then $[Q] \stackrel{\alpha}{\longleftrightarrow}\left[Q^{\prime}\right]$ and $\left[P^{\prime}\right] \sim\left[Q^{\prime}\right]$
2. $[Q] \stackrel{\alpha}{\hookrightarrow}\left[Q^{\prime}\right]$, then $[P] \stackrel{\alpha}{\longleftrightarrow}\left[P^{\prime}\right]$ and $\left[P^{\prime}\right] \sim\left[Q^{\prime}\right]$

- results are given in terms of ranges


## Results

- to show the full behaviour of a system $P^{(n)}, n$ must be greater than the sum of
- the maximum out-stoichiometry,
- the maximum in-stoichiometry, and
- the maximum in- or out-stoichiometry
- $C^{(n)} \bumpeq C^{(m)}$ if $n$ and $m$ are large enough
- $P^{(n)} \bumpeq P^{(m)}$ if $n$ and $m$ are large enough together with a technical condition required for stoichiometries larger than 1
- $\bumpeq$ is a congruence for $\xlongequal[*]{\mathscr{*}}$ if technical condition holds


## Example (revisited)



## Example (revisited)

$$
\begin{aligned}
& \begin{array}{l}
(5,0,0) \\
\stackrel{\alpha_{1}}{\rightleftarrows} \\
\alpha_{3} \downarrow \\
\alpha_{1} \\
\alpha_{3} \downarrow \\
\left.\alpha_{3} \downarrow, 0,1\right) \\
\stackrel{\alpha_{1}}{\rightleftarrows} \\
\alpha_{2} \\
\alpha_{1} \\
\alpha_{3} \downarrow \\
\hline
\end{array} \\
& (3,1,0) \underset{\alpha_{3}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(2,1,1) \underset{\alpha_{3}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,1,2) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,1,3) \\
& \alpha_{3} \downarrow \quad \alpha_{2} \alpha_{3} \downarrow \\
& (1,2,0) \underset{\alpha_{2}}{\rightleftarrows}(0,2,1)
\end{aligned}
$$

$$
\begin{aligned}
& \begin{array}{l}
(6,0,0)) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(5,0,1) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(4,0,2) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(3,0,3) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(2,0,4) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,0,5) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,0,6) \\
\alpha_{3} \downarrow \quad \alpha_{1} \downarrow \quad \alpha_{1} \downarrow \\
\alpha_{3} \\
\alpha_{1}
\end{array} \\
& (4,1,0) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(3,1,1) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(2,1,2) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,1,3) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,1,4) \\
& \alpha_{3} \downarrow \quad \alpha_{2} \alpha_{3} \downarrow \quad \alpha_{2} \alpha_{3} \downarrow \\
& (2,2,0) \underset{\alpha_{3}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,2,1) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,2,2) \\
& (0,3,0)
\end{aligned}
$$

## Example (revisited)

$$
\begin{aligned}
& \begin{array}{l}
(5,0,0) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(4,0,1) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(3,0,2) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(2,0,3) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,0,4) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,0,5) \\
\alpha_{\alpha_{2}} \\
\alpha_{3} \downarrow \\
\alpha_{1} \downarrow \\
\alpha_{3} \downarrow \\
\alpha_{1}
\end{array} \\
& \begin{array}{l}
(3,1,0) \\
\alpha_{3} \downarrow \quad \alpha_{\alpha_{2}} \alpha_{3} \downarrow
\end{array} \\
& (1,2,0) \underset{\alpha_{2}}{\rightleftarrows}(0,2,1)
\end{aligned}
$$

these are not compression bisimilar

$$
\begin{aligned}
& (4,1,0) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(3,1,1) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(2,1,2) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,1,3) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,1,4) \\
& \alpha_{3} \downarrow \quad \alpha_{2} \alpha_{3} \downarrow \quad \alpha_{2} \alpha_{3} \downarrow \\
& (2,2,0) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(1,2,1) \underset{\alpha_{2}}{\stackrel{\alpha_{1}}{\rightleftarrows}}(0,2,2) \\
& \alpha_{3} \downarrow \\
& (0,3,0)
\end{aligned}
$$

## Open problems

- hypothesis: if $T$ is the Icm for all stoichiometric coefficients, $n=m+c T$ for $c \in \mathbb{N}$ and $n, m$ large enough, then $P^{n} \bumpeq P^{m}$ can this be proved?


## Open problems

- hypothesis: if $T$ is the Icm for all stoichiometric coefficients, $n=m+c T$ for $c \in \mathbb{N}$ and $n, m$ large enough, then $P^{n} \bumpeq P^{m}$ can this be proved?
- can compression bisimulation be extended to an (approximate) quantitative equivalence?


## Open problems

- hypothesis: if $T$ is the Icm for all stoichiometric coefficients, $n=m+c T$ for $c \in \mathbb{N}$ and $n, m$ large enough, then $P^{n} \bumpeq P^{m}$ can this be proved?
- can compression bisimulation be extended to an (approximate) quantitative equivalence?
- are there other operators of interest?
- can two subpopulations, $C$ and $D$, be combined?
- define a new operator $C \boxplus D$
- must the actions of $C$ and $D$ be disjoint?
- can a single subpopulation have repeated actions?


## Open problems (continued)

- how can the notion of a stochastic population process algebra be made more general?
- what are the important aspects?
- can these be expressed by parameterising functions?
- choice of functions instantiates population process algebra
- provide meta-results with respect to these functions
- not as general as a SOS format


## More generally

$$
\begin{aligned}
& \begin{array}{l}
C(n) \xrightarrow{\alpha, \nu_{\alpha}^{C}(n)}{ }_{C} C\left(\mu_{\alpha}^{C}(n)\right) \\
\sum_{k=1}^{n_{C}} \beta_{k} \odot C \\
\text { ■ stoichiometric information and conditions no longer appear in } \\
\text { the prefix but are embedded in the definition of the function } \mu_{\alpha}^{C} \\
\text { - only local information about } C \text { can be used in } \mu_{\alpha}^{C} \text { and } \nu_{\alpha}^{C}
\end{array} \quad \quad \mu_{\alpha}^{C}(n) \text { and } \nu_{\alpha}^{C}(n) \text { are defined }
\end{aligned}
$$

$$
\begin{aligned}
& \frac{P \xrightarrow{\alpha, S}_{c} P^{\prime}}{P \underset{*}{\nVdash} Q \xrightarrow{\alpha, S} P^{\prime}{\underset{*}{\circledast}}^{\circledast} Q} \quad Q \xrightarrow{\alpha, S^{\prime}} c \\
& \frac{Q \xrightarrow{\alpha, S} c}{P} Q^{\prime} Q \xrightarrow{\alpha, S} P^{\prime}{\underset{*}{\circledast} Q}^{\otimes} \quad P{\xrightarrow{\alpha, S^{\prime}} c}_{c} \\
& \frac{P{\xrightarrow{\alpha, S_{1}}}_{c} P^{\prime} \quad Q \xrightarrow{\alpha, S_{2}} c Q^{\prime} Q^{\prime}}{P \xrightarrow{\otimes} Q \xrightarrow{\alpha, \rho_{\alpha}\left(S_{1}, S_{2}\right)}{ }_{c} P^{\prime}{\underset{*}{*}}^{*} Q^{\prime}}
\end{aligned}
$$

## More generally (continued)

$$
\frac{P \xrightarrow{\alpha, S}_{c} P^{\prime}}{P{\xrightarrow{\alpha, f_{\alpha}(S)}}_{s} P^{\prime}}
$$

- $f_{\alpha}: \mathcal{S} \rightarrow \mathbb{R}_{\geq 0}$
- Markov chain semantics are given by $\xrightarrow{\alpha, r}{ }_{s}$
- ODEs can be derived from $C_{1}\left(n_{1,0}\right) \nVdash_{*} \ldots \Vdash_{*} C_{p}\left(n_{p, 0}\right)$
- unspecified functions: $\nu_{\alpha}^{C}, \mu_{\alpha}^{C}, \rho_{\alpha}, f_{\alpha}$
- what are sensible choices in the context of population modelling?


## Open problems (continued)

- how can modelling of space in the context of smart transport and smart grids be combined with population modelling?


## Open problems (continued)

- how can modelling of space in the context of smart transport and smart grids be combined with population modelling?



## Thank you

