

# Network Modeling and Simulation

Ilaria Cherchi

Telegram: @ilariacherchi

Giacomo Fantoni

Telegram: @GiacomoFantoni

Elisa Pettinà

Telegram: @elispettina

Github: <https://github.com/giacThePhantom/network-modelling-and-simulation>

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# Part I

## Stochastic models

# Chapter 1

## Introduction

### 1.1 Introduction

#### 1.1.1 Cells

A cell is the basic unit of all known living organism. Different cell types have different roles which then organize to form higher levels of organization. The cell is a dynamical system whose behaviour is controlled and regulated by interaction between chemical species.

#### 1.1.2 Biochemical reactions

The interactions between molecules in a cell are known are biochemical reactions. The chemical species in a cells are in constant movement and when they collide can cause a reaction if specific reaction conditions, like the activation energy, are satisfied. The outcome of a reaction is the consumption of some species and the production of new ones to help perform the necessary activities of the cell.

##### 1.1.2.1 Reaction kinetics

The rate of a reaction is dependent on the species involved, the number of molecules present and a basal rate or affinity. The basal rate depends on the type and number of species involved and is often constant. The rates of reaction are determined by the reaction kinetics.

##### 1.1.2.2 Pathways

Biochemical reactions are organized in pathways, a map showing the structural relationship of molecular species and their specific cellular response. They are involved in:

- Metabolism.
- Signal transmission.
- Gene expression regulation.

They are involved in different cellular purposes like:

## 1.1. INTRODUCTION

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- Cell growth.
- Differentiation.
- Proliferation.
- Apoptosis.

Explaining how a cellular function emerges from the molecular interactions needs a system-wide approach.

### 1.1.3 Systems biology

Systems biology is a new discipline that aims to understand how reactions give rise to specific cellular behaviours and a biological response. Its holistic view-point provide advantages in scientific and practical terms like:

- Drug discovery.
- Hypothesis verification.
- Disease mechanism explanation.

#### 1.1.3.1 Challenges of system biology

The challenges of systems biology are due to the large number of possible reactions and their non-linear dynamics. In these cases the stationary and time-invariant assumptions are often violated: the species constantly evolves according to changes in the cellular environments. Moreover some molecular species are present in low copy number or population. Reaction between these cause a significant fluctuation in their population, or biological noise, which may propagate along the pathway.

#### 1.1.3.2 Stochasticity

The stochasticity in biochemical reaction can be also due to the fact that after many non-reactive collisions between species the biological system could choose a different cellular functioning. This is called multistability: a number of separated stable equilibria points are separated by unstable equilibria. Bistability is the simplest example of multistability, with only two stable equilibria.

### 1.1.4 Computational tools

Computational tools play a crucial role in systems biology. Introducing a model to represent the biological system's species of interest or states and the reaction between them or state transition, knowledge of the biology can be written in a formal form, often mathematically.

#### 1.1.4.1 Biological models

A biological model is an abstraction of the system, but it is useful to understand it. A direct way to describe a model is to write down the list of reactions between species. Modelling a reaction network by coupled reactions is simple and flexible.

#### 1.1.4.2 Computer simulation

Given a model, a computer simulation is used to realize its temporal evolution. The dynamical interactions between species can reveal indirect implications or unexpected behaviours. A simulation based experiment is called an *in silico* experiment. If results of this experiment agree with experimental data, they can be used to provide predictions for the dynamics of the system.

## 1.2. DIFFERENT LEVELS OF SIMULATION

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### 1.1.4.3 Advantages and applications of in silico experiment

With respect to traditional experiment, an in silico simulation has a number of advantages:

- It takes less time.
- It is cheaper.
- They can detect indirect and hidden implications.
- It is possible to isolate vital genes from the cell, overcoming the necessity of maintaining a vital cell.

The results of an in silico experiment are used to:

- Test hypothesis.
- Suggesting new experiments.

The predictive feature of computer simulations makes it useful to perform quantitative analysis.

### 1.1.5 Synthetic biology

Biological models and simulation contribute to the design and implementation of synthetic biology by providing a design focused experiment framework where models are reused as basic building blocks in a large model. This component-based model building is more effective and less error-prone than a traditional from-scratch approach. Moreover this component approach allows to reprogram cellular functions to serve for special purposes of biological research.

## 1.2 Different levels of simulation

To cope with the inherent multi-physics and multi-scale natures of biochemical reactions, different levels of simulation detail have been adopted to investigate their dynamical behaviour.

### 1.2.1 Molecular dynamics

Molecular dynamics deals with the microscopic level. In this type of simulation the structures, positions velocities and possible collisions of all molecules in the system are kept track of. Movement and reactions are governed by physical forces. A molecular dynamics simulation requires a very detailed knowledge of molecules in both time and space and requires a lot of computational power. Because of this it is used to simulate the system at the level of nanoscale of time and space.

### 1.2.2 Brownian dynamics

Brownian dynamics focuses on the dynamics of each individual species, skipping the molecular structure information and the weak long-range forces between species. The movement of a species is described as a random or Brownian walk among point-like structures. A reaction happens whenever the distance between two species is less than a predefined reaction radius. The time scale of a Brownian dynamics simulation is greatly improved over molecular dynamics, but it is still require too much computational power to deal with large scale models.

### 1.2.3 Deterministic simulation

A deterministic simulation is the highest coarse-grained approach which focuses on the macroscopic behaviour of biochemical reactions. Molecular species in the deterministic simulation approach are represented by their concentrations. The rate of change in the concentration of each species due to a reaction is directly proportional to the concentrations of the species involved in the reaction. The time evolution of a biochemical reaction network is described by a set of ordinary differential equations or ODEs. The deterministic simulation is fast, however its underlying assumption inherently oversimplifies biological reactions in which populations of molecular species are continuous variables and their changes due to single reaction firings are assumed to be negligible. The correctness of deterministic simulation is severely affected when stochasticity plays an important role in the dynamical behaviour of biochemical reactions.

### 1.2.4 Stochastic simulation

A stochastic simulation is a mesoscopic approach to provide a probabilistic description of the time evolution of biochemical reactions. It keeps track of a discrete count for the population, but abstracts all the detailed position and velocity information of each species. Each reaction in the network is assigned a non-negative chance to fire and to drive the system to a new state. The probability that a reaction occurs in a time interval is derived from the reaction kinetics. Each stochastic simulation step will select a reaction to fire according to its probability.

### 1.2.5 Problems with stochastic simulations

Although the stochastic simulation approach is faster than both a molecular dynamics or Brownian dynamics approach, it is often computational demanding for simulating large biological systems. Moreover:

- Biochemical reactions, due to their multi-scale nature, are separated by different time scales in which some fast reactions will occur at rates greater than other reactions. The dynamical behaviour of biochemical reactions, after the short fluctuation time at the beginning, will be determined by the dynamics of the slow reactions. However, most of the time the simulation samples the fast reactions to realize the dynamics which is not the expected behaviour.
- The population of some species involved in reactions may be larger than others by many orders of magnitude. This implies that the fluctuations of some species are more or less significant when involving reactions fire.
- Keeping track of large population species is less efficient, since a coarse-grained simulation method can be applied without loss of total simulation accuracy. A model can combine and mix all of these aspects making the fast reactions occur frequently and drive the system very fast into a stable state.
- Due to the stochastic behaviour in a single simulation, many simulation runs must be performed to ensure a statistical accuracy and this requires a high computational effort. These issues raise a computational challenge for developing and implementing efficient stochastic simulation methods.

## 1.3 Network modeling

[ missing lecture 2 ]

### 1.3.1 Logic models

Recap from the previous theory lecture: what is the main issue in using logic modelling with multiple levels? The update formulae need to be defined for each level, tricky extension procedure.

### 1.3.2 Petri nets

**Petri nets** are specific networks introduced in 1960s, with the idea to describe *communication processes* (computer science field). We have two kinds of nodes:

- **places**: container of entities
  - *tokens*: entities
- **transitions**: possibility to move one or more tokens to other places

In order to model a chemical reaction, we can associate places to variables, transitions to chemical transformations and tokens to molecules.

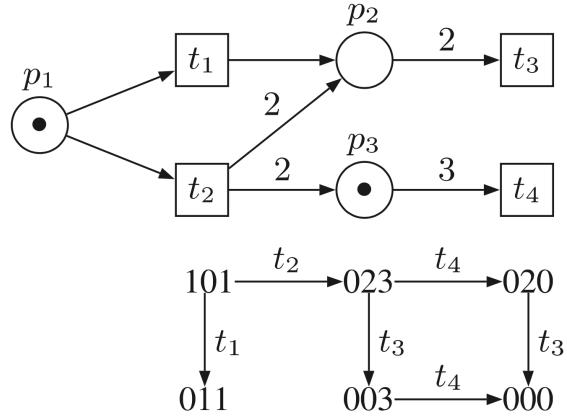
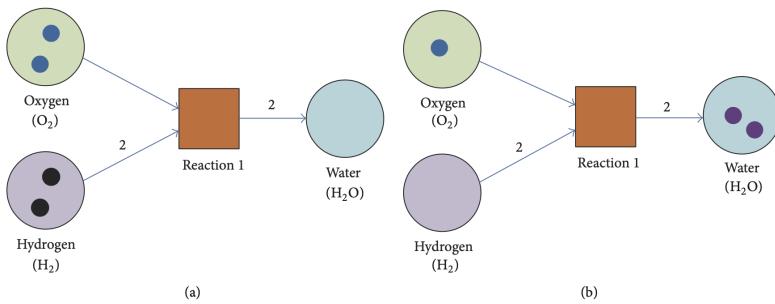


Figure 1.1: PetriNets\_SimaoEtAl.pdf

Figure 1.1: in the example we have numbers inserted in places. The network will evolve according to the transitions applied. A transition can be *enabled* or not to fire. E.g. there is one token in  $p_1$ , so we know that  $t_1$  and  $t_2$  are enabled. Instead,  $t_4$  cannot be enabled, as 3 tokens are required but only one is present.  $t_2$  is taking the token from  $p_1$  and creating 2 tokens in  $p_2$  and  $p_3$ ; this allows to fire  $t_4$ , since now  $p_3$  has the required number of tokens.

(a) shows the initial marking before firing the enable transition  $t$ ;

### 1.3. NETWORK MODELING



**Figure 1.2:** Review \_ ModelingComplexBiologicalSystems.pdf

(b) shows the marking after transition labeled reaction 1 fires. Places: hydrogen, oxygen and water. We can represent the stoichiometry of the reaction through the numbers on the edges and the numbers to the tokens.

Figure 1.2

- Pros: we have no constraint on the data type, not strictly boolean values. They allow to extend the number of items which can be associated to a model.
  - Cons: there is no fixed rule for applying transitions. Furthermore, we are not encoding the reaction's complexity (all transitions are equally probable, but it is possible to weight the edges).

Having a dynamics based on the integers can be quite useful, as if we consider single chemical events we are working with discrete data. The exact stochastic algorithm works with integers. In differential equations instead we need real numbers. Also the discretization of the time step might not be a limitation, since time can be discretized in reality. The main limitation of network models is the **approximation of time**, as we are assuming that all the reactions take the same (unknown) amount of time.

By upgrading the notation we can achieve more accurate representations:

- add inhibitory and test transitions.
  - differentiate between discrete and continuous transitions.

### 1.3.3 Rewriting systems

### 1.3.3.1 P systems

Popular rewriting systems are ***P* systems**, which are also called membrane systems. They are computational environments inspired to the structure of membranes. In particular, they define a hierarchy of membranes partitioning the space in different areas - similarly to a cell. In each region we can allocate entities and apply transformation rules. The rewriting rules change the value of each letter. The pedix *in4* gives more details on the reaction. These kind of systems tend to use *non-determinism*, they try to explore the full set of possibilities.

### 1.3. NETWORK MODELING

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#### 1.3.3.2 MP systems

The difference with standard P system is the association of functions to each reaction. In this way we can reconstruct the complexity of the reaction, since in the model we apply all possible reaction - which will produce an amount given by the function.

#### 1.3.4 Equation-based approach

##### 1.3.4.1 ODE systems

Example: mass-action model  $A + E \xrightleftharpoons[k_2]{k_1} A | E \xrightarrow{k_3} B + E$

#### 1.3.5 Simulation algorithms

For simulating we need the specification of a stoichiometric matrix, a vector of integers (initial values) and a stochastic rate. **Exact simulation algorithms** are computationally intensive, but provide the most accurate solution. Stepwise, we will try to define faster strategies with the aim of compromising accurate dynamics and feasible solutions. It is also possible to rely on a mixture of technologies to focus on different results. If the well-mixed assumption is not fulfilled:

- partition the compartment in sub-compartments → approximation
- use more sophisticated algorithms

The *stoichiometric matrix* tells us how the system evolves if one of the two functions is applied, but it is not enough for computing a simulation. There can be many reactions that arrive to the same definition of stoichiometric matrix. If we want to compute a dynamics we need to develop a series of states; at each step we require two ingredients:

- $\tau$ : tells how much later the system will evolve to another state
- $\mu$ : choose the reaction by considering the probability of execution of each reaction at the step

##### 1.3.5.1 Reaction propensity

The reaction propensity is a function needed for the derivation of probability. The higher the propensity, the higher will be the strength of the reaction. Naturally, we will have a higher probability when a higher propensity is observed, but the two quantities are something different. The propensity is a property of the reaction, probability is a property of a reaction in the system (we need to take into account also other reactions) Instead of performing an in depth analysis of probability, we will choose a stochastic approach. It is only necessary to compute one evolution of the system per time.

# Chapter 2

## Stochastic simulation of biochemical reaction systems

### 2.1 Introduction

Biochemical reaction network can be modelled through stochastic chemical kinetics. In this type of models the discreteness in population of species and the randomness of reactions are treated as an intrinsic part. The dynamical behaviour is described by the chemical master equation or CME.

### 2.2 Stochastic chemical kinetics

#### 2.2.1 Rewriting biochemical reactions

Biochemical reactions are the building blocks to model biological systems. They provide a unifying notation with sufficient level of details to represent complex biological processes. Biochemical reactions decorated with reaction kinetics can be simulated by a simulation algorithm to generate a realization of their dynamics. Chemical species in a biological system move around and gain kinetic energy. Upon collisions with other species, they undergo reactions to modify and transform into different species.

##### 2.2.1.1 Representing molecular reactions

Molecular reactions can be classified between elementary reactions and non-elementary ones. The former require one step to complete, while the latter require a higher order reactions or a multi-step one.

###### 2.2.1.1.1 Some elementary reactions

**2.2.1.1.1 Unimolecular reaction** An unimolecular reaction involves the transformation of one species into another. It can be represented as:



**2.2.1.1.1.2 Degradation** The degradation of a species is a special type of an unimolecular reaction in which a species is degraded:



Where the symbol  $\emptyset$  represents a species that is not considered in the model, probably because it is large and does not change over time.

**2.2.1.1.1.3 Synthesis** The synthesis of a species is another type of unimolecular reaction in which a species is synthesised:



This reaction is used to model the effects of the outside environment on system dynamics.

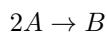
**2.2.1.1.1.4 Bimolecular reaction** An example of a bimolecular reaction is an association reaction, in which a molecule can associate with another to produce a complex:



Often this process is reversible and the inverse dissociation reaction can take place:

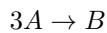


**2.2.1.1.1.5 Dimerization** The dimerization is a special bimolecular reaction in which two molecules of the same species are consumed to produce another species:

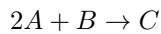


### 2.2.1.1.2 Some non-elementary reactions

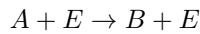
**2.2.1.1.2.1 Termolecular reaction** The thermolecular reaction is used to represent the polymerization of three molecules into another species. The original molecules can be of the same species:



Or of two different species:



**2.2.1.1.2.2 Enzymatic reaction** Another multi-step reaction is an enzymatic reaction, where the enzyme  $W$  that catalyses the rate of conversion is kept the same:



### 2.2.1.2 Equation-based methods

The previous way to represent reactions does not give insight on the function of the equation. To shine light on this aspect equation-based methods need to be applied, like ordinary differential equation systems. In these the derivative with respect to time is specified for any of the variables in term of a function of the state. It can be noted how the stochastic simulation approach can be approximated by a deterministic one.

### 2.2.1.3 Creating a formal mathematical description of a biological system

To write a mathematical description of a biological system there is a need to:

1. Choose the biochemical reactions' representation.
2. Choose the type of variable to describe the state of the system.
3. Specify the likelihood of execution for each reaction.

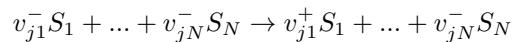
A reaction will be faster when there is a huge amount of reactants. This is because in term of probability: the more a species is present, the more it is likely to interact and for the reaction is to happen. This is true only when the assumption of that there is a well-mixed reaction volume is made. This assumption entails that the distribution of molecules is uniform. Moreover, in order to approximate a complex system the main compartments can be partitioned in smaller sets where a discretization procedure can be applied. Therefore in this case Petri nets are a suitable representation for these kind of systems.

### 2.2.1.4 Well-mixed reaction volume

A well-mixed reaction volume is a reaction volume in which all the molecular species are homogeneously distributed and spatially indistinguishable. This is legitimate as non-reactive conditions are much more frequent than reactive ones. The biochemical reaction system with well-mixed volume thus satisfies the spatial homogeneity condition, where spatial distribution of molecular species can be ignored. Chemical species under the well-mixed assumption at a thermal equilibrium are uniformly distributed in the volume  $V$  and their velocities are thermally randomized according to the Maxwell-Boltzmann distribution.

### 2.2.1.5 Formal representation

The state of a spatially homogeneous biological system is determined by the population of each species, while the position and velocity of each individual molecule are ignored. Let  $X_i(t)$  be the population of species  $S_i$  at a particular time  $t$ . The N-vector  $X(t) = (X_1(t), \dots, X_N(t))$ , which determines the population of each species, constitutes the system state at the time  $t$ . Chemical species interact through  $M$  reactions  $R_1, \dots, R_M$ . A general reaction  $R_j$  has a general scheme:



Where:

- Species on the left side are reactants.
- Species on the right side are products.
- The non-negative integers  $v_{ji}^-$  and  $v_{ji}^+$  are the stoichiometric coefficients which denote the number of molecules of a reactant that

## 2.2. STOCHASTIC CHEMICAL KINETICS

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are consumed and the number of molecules of a product that are produced.

A reactant species that affects the speed of a reaction but is not consumed by it is called a catalyst. The sum of stoichiometric coefficients of reactants of a reaction  $R_j$  is called reaction order. For each reaction  $R_j$ , the net change in the population of species  $S_i$  involved in the reaction is equal to  $v_{ji}^+ - v_{ji}^-$ , which can be positive, negative or zero.

### 2.2.1.6 Stoichiometric matrix

The net changes by all reactions are described by a stoichiometry matrix  $\vec{v}$  of size  $MN$ . The  $j$ th row  $\vec{v}_j$  of the stoichiometry matrix expresses the changes caused by reaction  $R_j$  and it is called the state change vector. Different system can lead to the same stoichiometric matrix. To describe a reaction two matrices are required:

- $V^+$  provides the products.
- $V^-$  provides the reactants.

$$V^- = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \end{bmatrix}, V^+ = \begin{bmatrix} 0 & 2 & 0 \\ 0 & 0 & 2 \\ 2 & 0 & 0 \end{bmatrix}, V = \begin{bmatrix} 1 & 1 & 0 \\ 0 & -1 & 1 \\ 1 & 0 & -1 \end{bmatrix} V = V^+ + V^-$$

Suppose that at a time  $t$  the state, or number of molecules in that given moment is  $X(t)$ . It is further assumed that the next reaction scheduled to fire at the next time  $t + \tau$  is  $R_\mu$ , which move the system accordingly to a new state  $X(t + \tau)$ .  $\vec{x}$  is a simple notation to represent  $X(t)$ . Two important assumptions are made for the transition from state  $X(t)$  to state  $X(t + \tau)$ :

- No changes occur in the system state during the time interval  $[t, t + \tau]$ , before the next reaction fires.
- The reaction occurs instantly after it is initiated.

These are called the Markov property. So the evolution of the system in a time step will be:

$$X(t + \tau) = X(t) + v_\mu$$

### 2.2.1.7 Summary

While specifying in computational terms the biological system of interest, the structure of at least one compartment has to be described, where it is assumed to find a chemical volume in which there are some entities that interact with each other. The he well-mixed volume preliminary assumption is enforced, meaning that all the actors are present with equal availability in all the parts of the volume. For each compartment, the entities or how many molecules are available, and the reactions that provide the rules for transforming the chemicals in others along the time have to be specified. All these structures of reactions can be defined in mathematical terms using matrices: the number of columns is equal to the number of variables, while the number of rows is equal to the number of reactions and the stoichiometric coefficient of the transformation from reactant to products is specified.

### 2.2.2 Reaction propensity

Each reaction in stochastic chemical kinetics is considered as a *stochastic process* where each of its occurrence is a random event with an assigned probability distribution. It is impossible to predict the progress of reactions deterministically, but only stochastically with a probability. The propensity of a reaction is a formula that is computed on a state of a system. Through the reaction propensity the probability of execution of a reaction will be hinted.

#### 2.2.2.1 Definition

The propensity  $a_j$  of a reaction  $R_j$  is defined such that  $a_j(x)dt$  is probability that a reaction  $R_j$  fires in the next infinitesimal time interval  $[t, t + dt]$ , given the state  $X(t) = \vec{x}$  at time  $t$ . In a chemical setting, the probability of execution of one reaction will be proportional to the viability of the reactant.

#### 2.2.2.2 Value of the propensity

The propensity  $a_j(X(T))$  is a function of the state  $X(t)$ . The fact that  $a_j$  of a reaction depends on time  $t$  happens implicitly through the Marcokian assumptions. At a particular time  $t$ , the value of the propensity  $a_j(X(T))$  is a deterministic quantity. The propensity value of a reaction in state  $X(t)$  is often used as a measure of how fast the reaction proceeds to move to a new state. Let  $\mathcal{P}\{R_j \text{ fires} \in [t, t + dt]\}$  be the probability that reaction  $R_j$  fires in the time interval. Given the state  $X(t) = \vec{x}$  at time  $t$ , then:

$$\mathcal{P}\{R_j \text{ fires} \in [t, t + dt]\} = a_j(\vec{x})dt + o(dt)$$

Where  $o(dt)$  expresses that it asymptotically approaches zero faster than  $dt$ :  $\lim_{dt \rightarrow 0} \frac{o(dt)}{dt} = 0$ . In other words the probability that there are more than one firing of  $R_j$  in the time step  $i$  in order of  $o(dt)$  and so it is negligible. The propensity of a reaction is an intrinsic property of the reaction and is linked to the phenomenon that the reaction is going to represent. The probability will depend on the propensity of the reaction and the other reactions that are competing for the same reactant. The propensity is not affected by the products.

$$a_1(0) = c_1 h_1(x(0))$$

$$h_2(x(0)) = \begin{pmatrix} 100 \\ 1 \end{pmatrix} \begin{pmatrix} 50 \\ 1 \end{pmatrix} \begin{pmatrix} 30 \\ 0 \end{pmatrix}$$

$$x(0 + \tau) = x(0) + V_1 = [99 \quad 51 \quad 30]$$

$$x(0) = [100 \quad 50 \quad 30]$$

Since the combination is being computed  $a^2$  will not be taken into account as in the canonical law of mass action.

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### 2.2.2.3 Mass action propensity

A precise formula for the propensity function  $a_j$  is dependent on the kinetics and a specific assumption about how the reaction occurs physically. This is referred as the fundamental premise of the stochastic chemical kinetics. For the standard mass action kinetics, the propensity  $a_j$  of reaction  $R_j$  is proportional to a stochastic reaction rate  $c_j$  and the number of its reactants. So given current state  $X(t)$  at time  $t$ :

$$a_j(X(t)) = c_j h_j(X(t))$$

Where  $c_j$  is the stochastic reaction rate and  $h_j(X(t))$  counts the number of distinct combination of reactants:

$$h_j(X(t)) = \prod_i \binom{X_i(t)}{v_{ji}^-} = \prod_i \frac{X_i(t)!}{v_{ij}^0!(X_i(t) - v_{ij}^-)!}$$

In the case of a synthesis reaction, where the stoichiometric coefficient of its reactants is 0 is set to  $h_j(X(t)) = 1$ .

**2.2.2.3.1 The stochastic rate** The stochastic rate  $c_j$  denotes the average probability per unit time that a particular combination of reactant molecules of reaction  $R_j$  reacts in the volume  $V$  and depends on the reaction type. In the case of a unimolecular reaction is independent of the volume size, while in the case of a bimolecular one it will be inversely proportional of it. The rate is constant provided that:

- The volume  $V$  is constant.
- The volume is thermally homogeneous.
- The volume is well-mixed.

### 2.2.2.4 Reaction propensity for reactions $R_j$ with mass action kinetics

From now  $X_i$  will be used in place of  $X_i(t)$ , when  $t$  is irrelevant or clear from the context. Some reaction will be described by mass action kinetics by:

- Synthesis reaction ( $\emptyset \rightarrow$  products): the number of combinations  $h_j = 1$  and propensity  $a_j = c_j$
- Unimolecular reaction ( $S_i \rightarrow$  products): the number of combinations  $h_j = X_i$  and propensity  $a_j = c_j X_i$ .
- Bimolecular reaction ( $S_i + S_k \rightarrow$  products): the number of combinations  $h_j = X_i X_k$  and propensity  $a_j = c_j X_i X_k$ .
- Dimerization reaction ( $2S_i \rightarrow$  products): the number of combinations  $h_j = \frac{1}{2} X_i (X_i - 1)$  and propensity  $a_j = \frac{1}{2} c_j X_i (X_i - 1)$ .
- Polymerization reaction ( $3S_i \rightarrow$  products): the number of combinations  $h_j = 16 X_i (X_i - 1)(X_i - 2)$  and propensity  $a_j = 16 c_j X_i (X_i - 1)(X_i - 2)$ .
- Termolecular reaction ( $2S_i + S_k \rightarrow$  products): the number of combinations  $h_j = \frac{1}{2} X_i (X_i - 1) X_k$  and propensity  $a_j = \frac{1}{2} c_j X_i (X_i - 1) X_k$ .

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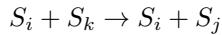
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### 2.2.2.5 Complex reaction kinetics

Complex reaction kinetics can be used. The propensity  $a_j$  will show a complicated, non-linear dependence on the chemical species and may contain more than one rate constant.

#### 2.2.2.5.1 Michaelis-Menten kinetics

The Michaelis-Menten kinetics is used to approximate the mechanism of enzymatic reaction. Consider an enzymatic reaction  $R_j$  with form:



Where:

- $S_k$  is the substrate.
- $S_i$  is the enzyme.

The reaction propensity will be defined as:

$$a_j = \frac{V_{\max}}{K_M + x_k} X_i X_k$$

Where:

- $V_{\max}$  is the maximum rate such that the substrate  $S_k$  is saturated.
- $K_m$  or Michaelis constant is the substrate concentration at which the reaction rate is half of  $V_{\max}$ .

## 2.2.3 Chemical Master Equation

The chemical master equation or CME is the theoretical approach allowing to derive the complete set of probabilities of all the possible states of the system. Suppose that the biochemical reaction system starts with an initial state  $X(t_0) = \vec{x}_0$ . Let  $t > t_0$  and the system at state  $X(t) = \vec{x}$ , The purpose of the stochastic chemical kinetics is to infer the probability:

$$\mathbb{P}\{\vec{x}, t | \vec{x}_0, t_0\}$$

### 2.2.3.1 Grand probability function

The probability function or grand probability:

$$\mathbb{P}\{\vec{x}, t | \vec{x}_0, t_o\}$$

Is the probability that the system state is  $X(t) = \vec{x}$  at time  $t$ , given the initial state  $X(t_0) = \vec{x}_0$  at time  $t_0$ . It is called so because it gives the probabilities of all reachable states of the system at time  $t$  given the initial state. Knowing it all the statistical properties can be computed for every species at any time.

### 2.2.3.2 Deriving the chemical master equation

To derive the time evolution of the grand probability, consider an infinitesimal time interval  $[t, t+dt]$  so that there is at most one reaction in that interval. Suppose that at time  $t+dt$  the system state is  $X(t+dt) = \vec{x}$ . There are two cases in order to reach the state  $\vec{x}$  in the time-step given the current time:

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- At time  $t$  the state is  $X(t) = \vec{x} - \vec{v}_j$  and reaction  $R_j$  fires in the next time step leading to  $X(t + dt) = \vec{x}$ .
- At time  $t$  the state is already  $X(t) = \vec{x}$  and no reaction fires in the time step.

Then the grand probability can be written as:

$$\begin{aligned}\mathbb{P}\{\vec{x}, t + dt | \vec{x}_0, t_0\} &= \sum_{j=1}^M \mathbb{P}\{R_j \text{ fires } \in [t, t + dt]\} \mathbb{P}\{\vec{x} - \vec{v}_j, t | \vec{x}_0, t_0\} + \\ &\quad + \mathbb{P}\{\text{No reaction fires } \in [t, t + dt]\} \mathbb{P}\{\vec{x}, t | \vec{x}_0, t_0\}\end{aligned}$$

Note that when the state vector  $\vec{x} - \vec{v}$  gives negative populations, the probability  $\mathbb{P}\{\vec{x} - \vec{v}_j, t | \vec{x}_0, t_0\}$  is zero because the populations of species must be positive. Now, the probability that no reaction fires in the time-step can be computed as:

$$\begin{aligned}\mathbb{P}\{\text{No reaction fires } \in [t, t + dt]\} &= \prod_{j=1}^M (1 - \mathbb{P}\{R_j \text{ fires } \in [t, t + dt]\}) = \\ &= \prod_{j=1}^M (1 - a_j(\vec{x})dt + o(dt)) = \\ &= 1 - \prod_{j=1}^M a_j(\vec{x})dt + o(dt)\end{aligned}$$

Then substituting the definition of the probability of a reaction firing and the probability of a reaction non firing just computed into the grand probability function:

$$\begin{aligned}\mathbb{P}\{\vec{x}, t + dt | \vec{x}_0, t_0\} &= \sum_{j=1}^M \mathbb{P}\{\vec{x} - \vec{v}_j, t | \vec{x}_0, t_0\} (a_j(\vec{x} - \vec{v}_j)dt + o(dt)) + \\ &\quad + \mathbb{P}\{\vec{x}, t | \vec{x}_0, t_0\} \left( 1 - \sum_{j=1}^M a_j(\vec{x})dt + o(dt) \right)\end{aligned}$$

Subtracting  $\mathbb{P}\{\vec{x}, t | \vec{x}_0, t_0\}$  from both sides, dividing by  $dt$  and considering the limit  $dt \rightarrow 0$ , the chemical master equation is obtained:

$$\frac{\mathbb{P}\{\vec{x}, t | \vec{x}_0, t_0\}}{dt} = \sum_{j=1}^M (a_j(\vec{x} - \vec{v}_j) \mathbb{P}\{\vec{x}, t | \vec{x}_0, t_0\} - \mathbb{P}\{\vec{x}, t | \vec{x}_0, t_0\} \sum_{j=1}^M a_j(\vec{x}))$$

The chemical master equation is a collection of differential equations in which each of them represents the probability of each possible state of the system at time  $t$ . It provides a complete description of the time evolution of the grand probability:

$$\mathbb{P}\{\vec{x}, t | \vec{x}_0, t_0\}$$

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#### 2.2.3.3 Limitations of the chemical master equation

The chemical master equation allows to compute the probabilities of all possible states at any time, however directly solving it require a lot of computational challenges:

- An analytical or numerical approach to solve CME in general is non-trivial to find.
- There is a huge number of differential equations:  $a^N$ , where  $N$  is the number of species and  $a$  is the values of the population of each species.

So it can be seen how the number of differential equations increases exponentially, making the state space explode in dimension, preventing direct approaches in solving CMEs.

## 2.3 Stochastic simulation

When applying the CME, all the possible state of the system are explored. With a stochastic simulation only one possible trajectory of the system are computed (to obtain the total description many simulations have to be run). The stochastic simulation works because only an idea of the most probable conditions of the system is needed. A stochastic simulation is faster than a real experiment and it can be run on a personal computer (also thousands of simulations can be performed). One of the crucial points of a stochastic simulation is that there is a need to be able to sample from this probability distribution function given the fact that the computer has few ways of generating something that is stochastic. The easiest way to do so is through a random number generator.

### 2.3.1 Probability density function

Stochastic simulations are an alternative approach to solve CME by producing possible realization of the grand probability function. It only explores possible states in the state space each time, so they can handle the biochemical reactions with very high-dimensional state space. The mathematical basis of a stochastic simulation is the reaction probability density function pdf:

$$p(\tau, \mu | \vec{x}, t)$$

Which is defined such that  $p(\tau, \mu | \vec{x}, t)d\tau$  is the probability that a reaction  $R_\mu$  fires in the next infinitesimal time interval  $[t + \tau, t + \tau + d\tau]$ , given the state  $X(t) = \vec{x}$  at time  $t$ . The pdf  $p(\tau, \mu | \vec{x}, t)$  is a joint distribution of two variables showing the index  $\mu$  of the reaction firing  $R_\mu$  at time  $\tau$  of the firing respectively, knowing that the system is at state  $X(t)$  at time  $t$ . The reaction index  $\mu$  will vary from  $1 \leq \mu \leq M$ , while the next time  $\tau$  will vary from  $0 \leq \tau \leq \infty$ .

#### 2.3.1.1 Computing the probability density function

The probability  $p(\tau, \mu | \vec{x}, t)dt$  can be computed as the product of:

- The probability that no reaction fires in the time interval  $[t, t + \tau[$ .
- The probability that a reaction  $R_\mu$  fires in the next infinitesimal interval  $[t + \tau, t + \tau + d\tau[$ .

Let:

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- $\mathbb{P}\{\text{No reaction fires } \in [t, t + \tau]\}$  be the probability that no reaction fires in the time interval  $[t, t + \tau]$ .
- $\mathbb{P}\{R_\mu \text{ fires } \in [t + \tau, t + \tau + d\tau]\}$  be the probability that reaction  $R_\mu$  fires in the next infinitesimal time interval  $[t + \tau, t + \tau + d\tau]$ .

Then:

$$p(\tau, \mu | \vec{x}, t) d\tau = \mathbb{P}\{\text{No reaction fires } \in [t, t + \tau]\} \mathbb{P}\{R_\mu \text{ fires } \in [t + \tau, t + \tau + d\tau]\}$$

To compute the probability that no reaction fires the time interval is divided into  $k$  non overlapping sub interval of length  $\epsilon = \frac{k}{\tau}$ . The probability that no reaction fires in the  $i$ -th interval  $[t + (i - 1)\epsilon, t + i\epsilon] \forall i = 1, \dots, k$  is:

$$\mathbb{P}\{\text{No reaction fires } \in [t + (i - 1)\epsilon, t + i\epsilon]\} = 1 - \sum_{j=1}^M a_j(\vec{x})\epsilon + o(\epsilon)$$

Hence the probability that no reaction fires in  $[t, t + \tau]$  is the product of the probabilities that no reaction fires in  $k$  non-overlapping intervals:

$$\begin{aligned} \mathbb{P}\{\text{No reaction fires } \in [t, t + \tau]\} &= \prod_{i=1}^k \mathbb{P}\{\text{No reaction fires } \in [t + (i - 1)\epsilon, t + i\epsilon]\} = \\ &= \prod_{i=1}^k \left( 1 - \sum_{j=1}^M a_j(\vec{x})\epsilon + o(\epsilon) \right) = \\ &= \left( 1 - \sum_{j=1}^M a_j(\vec{x})\epsilon + o(\epsilon) \right)^k = \\ &= (1 - a_0(\vec{x})\epsilon + o(\epsilon))^k \end{aligned}$$

Where  $a_0(\vec{x})$  is the total propensity defined as:

$$a_0(\vec{x}) = \sum_{j=1}^M a_j(\vec{x})$$

In the limit case where  $k \rightarrow \infty$ :

$$\begin{aligned} \mathbb{P}\{\text{No reaction fires } \in [t, t + \tau]\} &= \lim_{k \rightarrow \infty} (1 - a_0(\vec{x})\epsilon + o(\epsilon))^k = &= \lim_{k \rightarrow \infty} \left( 1 - \frac{a_0(\vec{x})k\epsilon + ko(\epsilon)}{k} \right)^k = \\ &= \lim_{k \rightarrow \infty} \left( 1 - \frac{a_0(\vec{x})\tau + \tau(\frac{o(\epsilon)}{\epsilon})}{k} \right)^k = \\ &= e^{-a_0(\vec{x})\tau} \end{aligned}$$

The last step is true because:

### 2.3. STOCHASTIC SIMULATION

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- $\frac{o(\epsilon)}{\epsilon} \rightarrow 0$  when  $k \rightarrow \infty$ .
- $\lim_{k \rightarrow \infty} \left(1 - \frac{a_0(\vec{x})\tau}{k}\right)^k = e^{-a_0(\vec{x})\tau}$ .

The probability that a reaction fires, following the definition of the reaction propensity is computed by:

$$\mathbb{P}\{R_\mu \text{ fires } \in [t + \tau, t + \tau + d\tau]\} = a_\mu(\vec{x})d\tau + o(d\tau)$$

Now plugging everything in the definition of the probability:

$$p(\tau, \mu | \vec{x}, t) d\tau = e^{-a_0(\vec{x})\tau} (a_\mu(\vec{x})d\tau + o(d\tau))$$

Dividing both sides by  $d\tau$  and taking the limit  $d\tau \rightarrow \infty$  and remembering that  $\frac{o(d\tau)}{d\tau} \rightarrow 0$ , the pdf will have the formula:

$$p(\tau, \mu | \vec{x}, t) = a_\mu(\vec{x})e^{-a_0(\vec{x})\tau}$$

Which is the joint probability density function of the next reaction index  $\mu$  and the next firing time  $\tau$  over their domains. This can be verified as:

$$\int_0^\infty d\tau \sum_{\mu=1}^M p(\tau, \mu | \vec{x}, t) = \sum_{\mu=1}^M a_\mu(\vec{x}) \int_0^\infty d\tau e^{-a_0(\vec{x})\tau} = 1$$

The pdf depends on the propensities of all reaction as well as on all species.

#### 2.3.2 Stochastic simulation algorithm

$$p(\tau, \mu | \vec{x}, t) = a_\mu(\vec{x})e^{-a_0(\vec{x})\tau}$$

Is the framework for a class of exact Monte Carlo simulation techniques originating from the stochastic simulation algorithm or SSA. It is a discrete event simulation: the state is updated by a random selected reaction  $R_\mu$  and a discrete time  $\tau$  sampled from the pdf. It exactly generates  $\mu$  of the reaction and the firing time  $\tau$  without introducing approximation in sampling the pdf. A general sketch of the SSA procedure is outlined in algorithm 1.

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**Algorithm 1: Stochastic simulation algorithm (SSA) - General Sketch()**

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- 1 **Input:** a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$
  - 2 **Output:** a trajectory of the biochemical reaction network which is a collection of states  $X(t)$  for time  $0 \leq t \leq T_{\max}$
  - 3  $t = 0$
  - 4  $\vec{X} = \vec{x}_0$
  - 5 **while**  $t < T_{\max}$  **do**
  - 6    $a_0 = 0$
  - 7   **foreach**  $R_j$  **do**
  - 8     compute  $a_j$
  - 9      $a_0 = a_0 + a_j$
  - 10   sample reaction  $R_\mu$  and firing time  $\tau$  from  $p(\tau, \mu, | \vec{x}, t)$
  - 11    $\vec{X} = \vec{X} + \vec{v}_\mu$
  - 12    $t = t + \tau$
-

## 2.4. SIMULATION OUTPUT ANALYSIS

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For each iteration in the while loop the algorithm computes the propensity  $a_j$  for each reaction and the total propensity. The next reaction  $R_\mu$  and its firing time  $\tau$  are sampled from the pdf, a step that may need the generation of randomly distributed random numbers. The state is updated and the time is advanced to  $t = t + \tau$ . The loop is repeated until  $t > T_{\max}$ . The propensities are updated at each iteration to reflect changes in the populations of species caused by reaction firings, but this can be skipped by employing an appropriate sampling technique. The result of the algorithm is a trajectory, that shows the evolution of the biological system over time. This is a collection of states  $X(t)$  that denotes the state of the system at any time  $0 \leq t \leq T_{\max}$ . It should be emphasized that because SSA is a discrete event simulation algorithm, the state changes only at discrete time instants when reactions fire. The state between two reaction firings is a constant.

## 2.4 Simulation output analysis

The trajectory obtained from a SSA run represents a possible realization of the grand probability  $\mathbb{P}\{\vec{x}, t | \vec{x}_0, t_0\}$ . Many independent runs started with the same initial conditions are needed to have a reasonable statistical estimation.

### 2.4.1 Confidence interval estimation

Let  $K$  be the number of simulation and  $\vec{X}^r$ , with  $r = 1, \dots, K$  be a realization of the state  $\vec{X}$  obtained at time  $t$  by the  $r$ -th independent run of SSA. The statistical properties can be derived from the ensemble of the trajectories, that are ensured to approach the exact solution of the CME as  $K \rightarrow \infty$ . Let  $\langle \vec{X} \rangle$  be the sample mean and  $s^2$  the unbiased variance. They are computed as:

$$\langle \vec{X} \rangle = \frac{\sum_{r=1}^K \vec{X}^r}{K} \quad s^2 = \frac{\sum_{r=1}^K (\vec{X}^r - \langle \vec{X} \rangle)^2}{K-1}$$

The sample mean and variance will approach the mean and variance of the random variable  $\vec{X}$  when  $K$  tends to infinity:

$$\mathbb{E}[\vec{X}] = \lim_{K \rightarrow \infty} \langle \vec{X} \rangle \quad \text{Var}[\vec{X}] = \lim_{K \rightarrow \infty} s^2$$

The convergence of the estimation is measured by the size of the confidence interval as the number of simulation runs is limited:

$$d = \frac{zs}{\sqrt{K}}$$

Where  $z$  is a confidence interval, denoting the percentage of the range of estimated values expected to include the true value. When it is fixed, the probability that the mean lies in the interval  $[\langle \vec{X} \rangle - d, \langle \vec{X} \rangle + d]$  is  $2\phi(z) - 1$ , where  $\phi$  is the cumulative distribution function or cdf of the normal distribution  $\text{norm}(0, 1)$ . The required number of simulation runs to achieve a specified confidence interval size can be computed:

$$K = \frac{z^2 s^2}{d^2}$$

$K$  depends reciprocally on the square of the confidence interval size  $d$  and on the sample variance  $s^2$ , which is unknown. One approach to circumvent this problem is to perform first a small number of trial runs to estimate  $s_{trial}^2$ , which is applied to compute the number of simulation runs necessary:

$$K = \frac{z^2 s_{trial}^2}{d^2}$$

### 2.4.2 Probability distribution equation

Bistability is a form of multistability where two separated stable equilibrium points are separated by an unstable equilibrium, the average population of species might not provide enough information for their dynamical behaviour. The probability distribution must be used to quantitatively analyse the simulation results. The probability distribution can be estimated by using the histogram or empirical distribution function of the samples. It is ensured to converge to the exact probability distribution given a large number of simulation runs  $K$ . The following assumes  $X$  to be a scalar value, but it can be easily extended to the general case. To compute the histogram the state  $X$  at time  $t$  obtained by  $K$  simulation runs of SSA is supposed to be bounded into an interval  $[X_{\min}, X_{\max}]$ , chosen arbitrarily. Then the interval is divided into  $B$  bins, such that the  $i$ -th bin  $I_i$  is defined as the subinterval:

$$\left[ X_{\min} + \frac{(i-1)L}{B}, X_{\min} + \frac{iL}{B} \right]$$

Where  $L = X_{\max} - X_{\min}$ . The histogram  $h_X$  of state  $X$  is then defined as:

$$h_X(I_i) = \frac{B}{KL} \sum_{r=1}^K \mathcal{X}(X^r, I_i)$$

Where  $X^r$  is the realization of  $X$  by the  $r$ -th simulation and  $\mathcal{X}(X^r, I_i)$  is defined as:

$$\mathcal{X}(X^r, I_i) = \begin{cases} 1 & X^r \in I_i \\ 0 & \text{otherwise} \end{cases}$$

The histogram therefore gives the average probability of  $X$  in interval  $I_i$ . Let now  $p_X$  be the probability distribution of state  $X$ . When  $K \rightarrow \infty$  and  $B \rightarrow \infty$ ,  $I_i$  reduces to a point and  $h_X$  converges to  $p_X$  at this point. Formally:

$$p_X = \lim_{K,B \rightarrow \infty} h_X$$

# Chapter 3

## Implementation of the Stochastic Simulation Algorithms

### 3.1 Introduction

#### 3.1.1 Non-deterministic vs stochastic

Working under the assumption of using the same model and parameters:

- A deterministic system does not show randomness and the same result is always obtained.
- A non-deterministic system shows some degree of uncertainty: different runs have different results.

##### 3.1.1.1 Exact stochastic simulation

In an exact stochastic simulation, if some hypotheses are satisfied the system will behave like the biological one. Although the probability function could be computed, this does not make the method deterministic: uncertainty is intrinsic in the model. Theoretically there is no insight on the execution of the reactions in a stochastic setting, but a high level of accuracy can be reached thanks to the probability function.

##### 3.1.2 Advantages of a non-deterministic approach

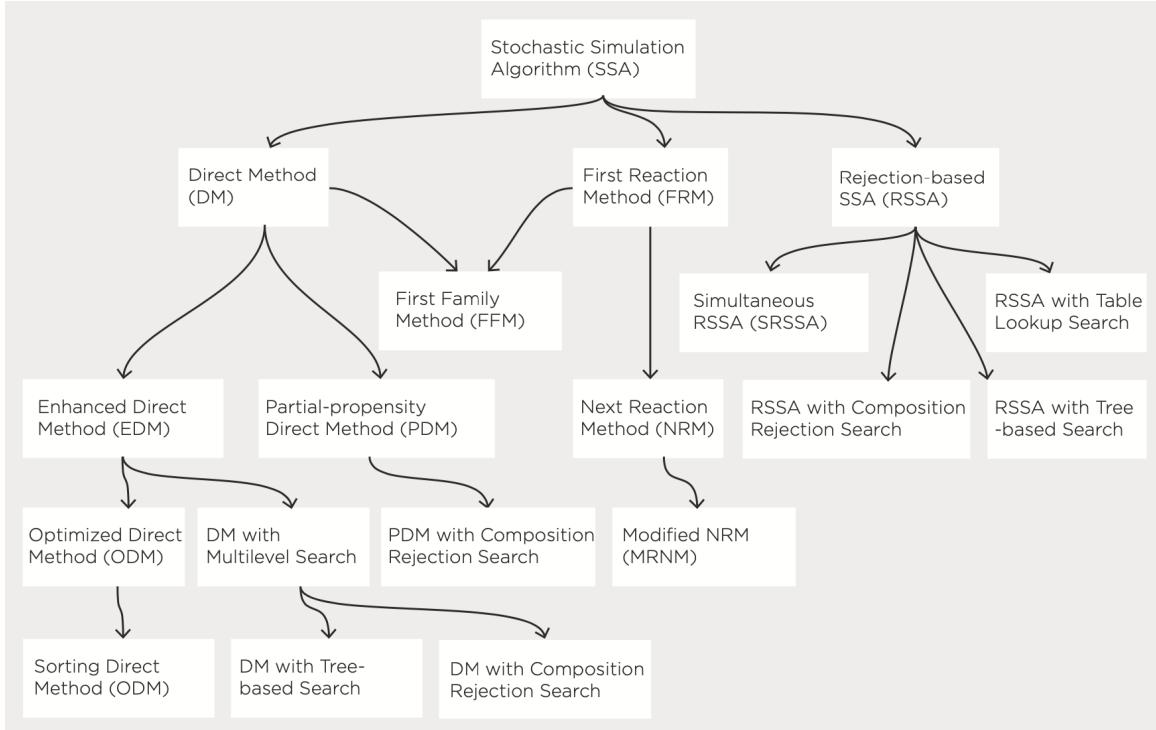
The reasoning behind the employment of a non-deterministic approach lies in the fact that to model a biological system there is a need to compromise between time and complexity. In non-deterministic polynomial time algorithms don't have an efficient solution, but it seems possible to find it. A non-deterministic setting allows us to understand whether an algorithm can be solved in polynomial time by step-wise guessing.

##### 3.1.3 Categories of the exact simulation algorithms

A summary of the main exact stochastic simulation algorithms is reported in figure 3.1.

### 3.2. DIRECT METHOD

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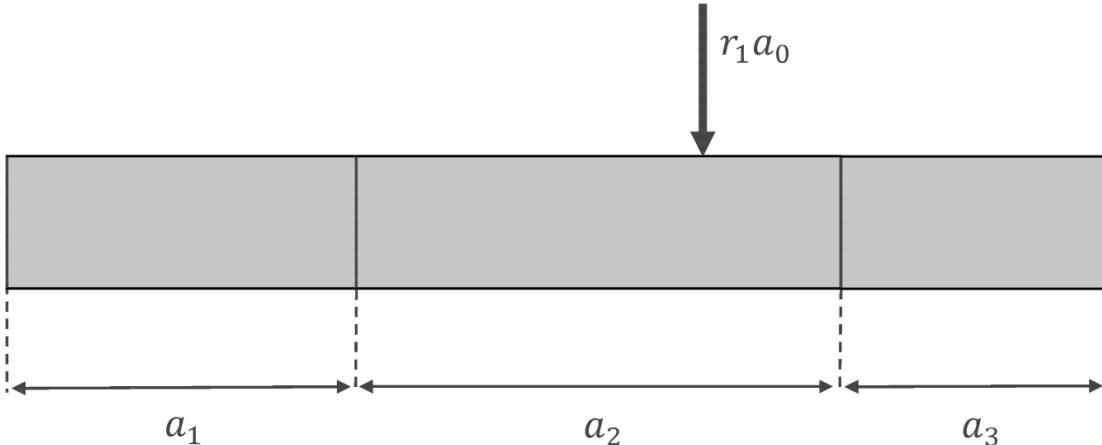


**Figure 3.1:** Main stochastic simulation algorithm.

## 3.2 Direct method

Gillespie's direct method defines a couple of formulae able to understand how the system will execute in terms of time  $\tau$  and reactions  $\mu$ . Since each time step is infinitesimal each reaction occurs and ends exactly at time  $\tau$ , hence there cannot be multiple reactions firing simultaneously. Let  $a_0$  be the sum of all propensities in the system, then the algorithm works as follow:

1. Sample one random number from the distribution  $a_0 = \sum_{j=1}^M a_j \rightarrow V_1 = U(0, 1)$ .
2. Scale it to the maximum  $V_1 \cdot a_0 = U(0, a_0)$ .
3. See where this number will point over the different propensities ( Figure 3.2).



**Figure 3.2:** Boundaries on the propensities.

4. Generate another random number  $V_2 = U(0, 1)$
5.  $\tau \sim Exp(a_0)$
6.  $\tau = \frac{1}{a_0} \ln(\frac{1}{V_2})$ .

### 3.2.1 Mathematical discussion

Gillespie's direct method is used to sample the pdf  $p(\tau, \mu | \vec{x}, t)$ . The direct method partitions the joint probability density function into the product of two one-variable probability functions, one for  $\tau$  and one for  $\mu$  that can be sampled independently. The pdf can be factorized by the chain rule of probability as:

$$p(\tau, \mu | \vec{x}, t) = p_1(\tau | \vec{x}, t) p_2(\mu | \vec{x}, t)$$

Where:

- $p_1$  is the probability density function of the firing time  $\tau$ .
- $p_2$  is the probability density function of the reaction with index  $\mu$  that fires at  $t + \tau$ .

So that  $p_1(\tau | \vec{x}, t) d\tau$  is the probability that a reaction will fire in the next time interval  $[t + \tau, t + \tau + d\tau]$ . This marginal probability is obtained by summing the probability  $p(\tau, \mu | \vec{x}, t) d\tau$  over the domain of all possible values of reaction index  $\mu$ :

$$p(\tau | \vec{x}, t) = \sum_{\mu=1}^M p(\tau, \mu | \vec{x}, t) = \sum_{\mu=1}^M a_\mu e^{a_0 \tau} = a_0 e^{-a_0 \tau}$$

Where  $a_0$  is the total propensity. Plugging this and recalling the formula of the joint pdf:

$$p_2(\mu | \tau, \vec{x}, t) = \frac{p(\tau, \mu | \vec{x}, t)}{p_1(\tau | \vec{x}, t)} = \frac{a_\mu}{a_0}$$

### 3.2. DIRECT METHOD

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It can be seen how  $p_2$  is independent of  $\tau$ , so it can be written as:

$$p_2(\mu|\vec{x}, t) = p_2(\mu|\tau, \vec{x}, t) = \frac{a_\mu}{a_0}$$

To verify that these two equation are part of the pdf:

$$\int_0^\infty p_1(\tau|\vec{x}, t)d\tau = \int_0^\infty a_0 e^{-a_0 \tau} d\tau = 1 \quad \wedge \quad \sum_{\mu=1}^M p_2(\mu|\vec{x}, t) = \sum_{\mu=1}^M \frac{a_\mu}{a_0} = 1$$

The direct method uses  $p_1(\tau|\vec{x}, t)$  to sample the firing time  $\tau$  and  $p_2(\mu|\vec{x}, t)$  to sample the reaction index  $\mu$ . Since the two pdfs are independent the firing time and the reaction index can be sampled independently, so that the order of sampling does not effect the exactness of the direct method. The generated firing time  $\tau$  and the next reaction firing  $R_\mu$  are ensured to have the pdf  $p(\tau, \mu|\vec{x}, t)$  specified by the stochastic simulation algorithm, so that the generated trajectories are exact.

#### 3.2.1.1 Choice of the reaction

The selection of the next reaction index  $\mu$  has probability  $\frac{a_\mu}{a_0}$ . Given  $M$  discrete probabilities  $\frac{a_j}{a_0}$  with  $j = 1, \dots, M$ , the choice of the next reaction index:

$$\begin{aligned} \mu &= \arg \min_{\mu \in j=1, \dots, M} \sum_{j=1}^M \frac{a_j}{a_0} \geq r_1 = \\ &= \arg \min_{\mu \in j=1, \dots, M} \sum_{j=1}^M a_j \geq r_1 a_0 \end{aligned}$$

Where  $r_1$  is a uniformly distributed random number  $norm(0, 1)$ . To select the next reaction firing  $R_\mu$ , the direct methods accumulates the sum  $\sum_{j=1}^\mu a_j$  until it finds the smallest index  $\mu$  that satisfies that inequality.

#### 3.2.1.2 Selection of the firing time

For the reaction of the firing time  $\tau$ , consider its pdf  $p_1(\tau|\vec{x}, t)$ . It can be noted ho it is an exponential distribution with rate  $a_0$ . So the firing time can be generated as:

$$\tau = \frac{1}{a_0} \ln \frac{1}{r_2}$$

Where  $r_2$  is a uniformly distributed random number  $norm(0, 1)$ .

#### 3.2.2 The algorithm

The independent sampling of the firing time and of the reaction index are the basis of each simulation step of the direct method, outlined in algorithm 2.

### 3.2. DIRECT METHOD

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**Algorithm 2:** Direct Method (DM) ()

---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$ 
2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$ 
3  $t = 0$ 
4  $\vec{X} = \vec{x}_0$ 
5 while  $t < T_{\max}$  do
6    $a_0 = 0$ 
7   foreach  $R_j$  do
8     compute  $a_j$ 
9      $a_0 = a_0 + a_j$ 
10  generate two random numbers  $r_1, r_2 \sim \text{norm}(0, 1)$ 
11  select  $R_\mu$  with the smallest index  $\mu$  such that  $\sum_{j=1}^{\mu} a_j \geq r_1 a_0$ 
12   $\tau = \frac{1}{a_0} \ln \frac{1}{r_2}$ 
13   $\vec{X} = \vec{X} + \vec{v}_\mu$ 
14   $t = t + \tau$ 

```

---

Lines 10-12 implement the sampling of the joint reaction probability density function of the next reaction firing and its firing time. The simulation needs two random number, the first is used to select the next reaction firing with probability  $\frac{a_\mu}{a_0}$ , while the second for the firing time. The state is then advanced to the new one and the time is moved to  $t + \tau$ .

#### 3.2.2.1 Time complexity

The computational cost for the generation of random numbers, the firing time and the update of simulation time are constant. Moreover the update of the state can be considered constant as only a few species are involved in a reaction. Because of this the computational cost of the algorithm arises due to:

- The computation of reaction propensities due to state changes at lines 7-9.
- The selection of the next reaction firing at line 11.

The direct method computes  $M$  reaction propensities for each simulation step, so the time complexity for this step is of  $O(M)$ . The search for the next reaction in the worst case requires to sum up all the  $M$  reaction propensities, making the cost for searching the next reaction firing  $O(M)$ . Summing up the time complexity for each simulation step of the direct method is  $O(M)$ .

#### 3.2.3 Enhanced direct method

The enhanced direct method EDM reduces the number of propensity computation for each simulation iteration, recomputing only the propensity of reactions that change. The detection of changes in the reaction propensity is based on the fact that the propensity of a reaction changes only when the population of the reactants involved in the reaction changes only then the population of the reactants involved are changed by the reaction firing. Only the propensity of reaction that have reactant

## 3.2. DIRECT METHOD

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population changed are recomputed. This is decided by analysing the dependency relationship between reactions.

### 3.2.3.1 Reaction dependency graph

A reaction  $R_j$  is dependent on a reaction  $R_\mu$  if its propensity  $a_j$  is changed when  $R_\mu$  fires. This relationship is collected and presented in a reaction dependency graph.

#### 3.2.3.1.1 Some definitions

##### 3.2.3.1.1.1 Reactants and products set

For each reaction  $R_j$ , with  $j = 1, \dots, M$ , define:

$$Reactants(R_j) = \{S_i | S_i \text{ is a reactant of } R_j\} \quad \wedge \quad Products(R_j) = \{S_i | S_i \text{ is a product of } R_j\}$$

##### 3.2.3.1.1.2 Affects set

The set of species involved in the computation of the propensity  $a_j$  of a reaction  $R_j$  is:

$$Affects(R_j) = \{S_i | a_j \text{ changes if population of } S_i \text{ changes}\}$$

##### 3.2.3.1.1.3 Mass action kinetics

For mass action kinetics, because the mass action propensity  $a_j$  of reaction  $R_j$  is proportional to its reactants:

$$Affects(R_j) = Reactants(R_j)$$

##### 3.2.3.1.1.4 AffectedBy set

The set of species whose population changes by firing reaction  $R_j$  is:

$$AffectedBy(R_j) = \{S_i | \text{Population of } S_i \text{ is changed if firing } R_j\}$$

##### 3.2.3.1.1.5 Population of AffectedBy

For each reaction  $R_j$  it is:

$$AffectedBy(R_j) \subseteq Reactants(R_j) \cup Products(R_j)$$

This is because  $AffectedBy(R_j)$  includes species that are consumed and produced by reaction  $R_j$  excluding any species whose population is conserved.

##### 3.2.3.1.2 Definition of the reaction dependency graph

Let  $\mathcal{R}$  be the set of reactions in the biochemical reaction network. The reaction dependency graph  $G(V, E)$  is a directed graph with the vertex set  $V = \mathcal{R}$  and the edge set  $E$  contains directed edges  $e(R_j, R_k)$  from a reaction  $R_j$  to another reaction  $R_k$  if:

$$AffectedBy(R_j) \cap Affects(R_k) \neq \emptyset$$

All self-edges  $e(R_j, R_j)$  belong to  $E$ .

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**3.2.3.1.3 Dependent reactions** The set of reactions that are dependent on reaction  $R_j$  by the reaction dependency graph  $G$  is defined such that:

$$\text{Dependents}(R_j) = \{R_k \mid \exists \text{ a directed edge } e(R_j, R_k) \in G\}$$

The reaction dependency graph  $G$  determines the reaction for which propensities must be recomputed after firing. The number of reaction in the *Dependents* set is equal to the out-degree of the reaction in the dependency graph.

### 3.2.3.2 Algorithm

In the EDM algorithm the reaction dependency graph is the first thing built. This will be a static structure independent on the time evolution of the system and will be stored with a cost  $O(M^2)$ . The computation of propensity of all the reaction is performed only at the beginning of the simulation. For each iteration the selection is the same as in DM, then the new propensity for each reaction  $R_j \in \text{Dependents}(R_\mu)$  is computed. The algorithm is presented in 3.

---

#### Algorithm 3: Enhanced Direct Method (EDM) ()

---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$ 
2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$ 
3 build the reaction dependency graph  $G$ 
4  $t = 0$ 
5  $\vec{X} = \vec{x}_0$ 
6 foreach  $R_j$  do
7   compute  $a_j$ 
8    $a_0 = a_0 + a_j$ 
9 while  $t < T_{\max}$  do
10   generate two random numbers  $r_1, r_2 \sim \text{norm}(0, 1)$ 
11   select  $R_\mu$  with the smallest index  $\mu$  such that  $\sum_{j=1}^{\mu} a_j \geq r_1 a_0$ 
12    $\tau = \frac{1}{a_0} \ln \frac{1}{r_2}$ 
13    $\vec{X} = \vec{X} + \vec{v}_\mu$ 
14    $t = t + \tau$ 
15   foreach  $R_j \in \text{Dependents}(R_\mu)$  do
16     compute  $a_j^{new}$ 
17      $a_0 = a_0 + (a_j^{new} - a_j)$ 
18      $a_j = a_j^{new}$ 

```

---

In this way the propensity updates become local. Let  $D$  be the average number of reactions depending in a reaction, the cost of the propensity update for a simulation loop becomes  $O(D)$ , considering that  $D < M$ , so the propensity update in EDM is more efficient than in DM.

## 3.2. DIRECT METHOD

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### 3.2.4 Improvements for Direct Method

#### 3.2.4.1 Direct method with sorted reaction

The principle of the direct method with sorted reaction is to reduce the search depth of the direct method by re-indexing reactions, reducing the search depth of reactions that happens more frequently, improving simulation performance.

**3.2.4.1.1 Optimized direct method** The optimized direct method reduces the average search depth of the next reaction firing. This is done because in many biochemical networks, some reactions fire much more frequently than others.

**3.2.4.1.1.1 Average search depth** The average search depth  $S_m$  is the average number of operation performed for the selection of the next reaction firing:

$$S_M = \frac{\sum_{j=1}^M j n_j}{\sum_{j=1}^M n_j}$$

Where:

- $j$  is the search index of reaction  $R_j$ .
- $n_j$  is the number of times that  $R_j$  fires during the simulation.

These two values are not known so to order the reactions  $\langle n_j \rangle$  the average estimation of  $n_j$  is used to order reaction. This is computed by some short pre-simulation runs.

**3.2.4.1.1.2 Algorithm** Optimized direct method is implemented as in algorithm 4.

## 3.2. DIRECT METHOD

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**Algorithm 4:** Optimized Direct Method (ODM)()

---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$   

2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$   

3 build the reaction dependency graph  $G$   

4 perform a few DM pre-simulation runs to estimate  $\langle n_j \rangle$  of each reaction  

5 order reaction indices such that  $j < k$  if  $\langle n_j \rangle > \langle n_k \rangle$   

6  $t = 0$   

7  $\vec{X} = \vec{x}_0$   

8 foreach  $R_j$  do  

9   | compute  $a_j$   

10  |  $a_0 = a_0 + a_j$   

11 while  $t < T_{\max}$  do  

12   | generate two random numbers  $r_1, r_2 \sim \text{norm}(0, 1)$   

13   | select  $R_\mu$  with the smallest index  $\mu$  such that  $\sum_{j=1}^{\mu} a_j \geq r_1 a_0$   

14   |  $\tau = \frac{1}{a_0} \ln \frac{1}{r_2}$   

15   |  $\vec{X} = \vec{X} + \vec{v}_\mu$   

16   |  $t = t + \tau$   

17   | foreach  $R_j \in \text{Dependents}(R_\mu)$  do  

18     |   | compute  $a_j^{new}$   

19     |   |  $a_0 = a_0 + (a_j^{new} - a_j)$   

20     |   |  $a_j = a_j^{new}$ 

```

---

**3.2.4.1.1.3 Discussion** In the case of a fixed number of bits the sum of the biggest propensities placed in the front of the search list may be not enough to account for the rest: the reactions with very small propensity will never fire. Moreover the pre-simulation introduces an additional computational burden to the simulation. Moreover ODM assumes that the reaction order determined by the pre-simulation runs will characterize the long-term reaction behaviour, which could not be true.

**3.2.4.1.2 Sorting direct method** The sorting direct method SDM is a variant of ODM that does not use pre-simulation runs by maintaining an approximately sorted order of reaction. The ordering is built dynamically during the simulation run: the index of a reaction whenever it is selected to fire is dynamically bubbled up one step ahead in the reaction list. The reactions that have just occurred are put towards the top of the search list.

**3.2.4.1.2.1 Algorithm** The sorting direct method is implemented as in algorithm 5.

### 3.2. DIRECT METHOD

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**Algorithm 5:** Sorting Direct Method (SDM) ()

---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$   

2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$   

3  $t = 0$   

4  $\vec{X} = \vec{x}_0$   

5 build the reaction dependency graph  $G$   

6 foreach  $R_j$  do  

7   | compute  $a_j$   

8   |  $a_0 = a_0 + a_j$   

9 while  $t < T_{\max}$  do  

10  | generate two random numbers  $r_1, r_2 \sim \text{norm}(0, 1)$   

11  | select  $R_\mu$  with the smallest index  $\mu$  such that  $\sum_{j=1}^{\mu} a_j \geq r_1 a_0$   

12  |  $\tau = \frac{1}{a_0} \ln \frac{1}{r_2}$   

13  |  $\vec{X} = \vec{X} + \vec{v}_\mu$   

14  |  $t = t + \tau$   

15  | foreach  $R_j \in \text{Dependents}(R_\mu)$  do  

16    |   | compute  $a_j^{new}$   

17    |   |  $a_0 = a_0 + (a_j^{new} - a_j)$   

18    |   |  $a_j = a_j^{new}$   

19  | if  $\mu > 1$  then  

20    |   | Swap  $R_\mu$  and  $R_{\mu-1}$  in the reaction list

```

---

**3.2.4.1.2.2 Discussion** The swapping step adds overhead to each simulation step, but it is negligible. SDM is thus suited to deal with the simulation of networks where the propensities change sharply.

#### 3.2.4.2 Direct method with Multi-level search

The main bottleneck of DM is that the search for next reaction firing is slow in large reaction models. The multi-level search is an effort to reduce the time complexity of DM for large systems. The search problem is divided into smaller sub-problem partitioning the  $M$  reactions into  $L$  groups  $G_1, \dots, G_L$ . Each group  $G_l$  contains  $k_l$  reactions. Let  $a^l$  be the sum of propensities of reactions in group  $G_l$ :

$$a^l = \sum_{R_j \in G_l} a_j$$

It is obvious that:

$$a_0 = \sum_{l=1}^L a^l$$

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The selection of the next reaction firing is in two steps. First a group  $G_\alpha$  is selected with probability  $\frac{a^\alpha}{a_0}$ . Then the next reaction firing  $R_\mu$  is selected with probability  $\frac{a_\mu}{a^\alpha}$  conditioning on the selected group  $G_\alpha$ .

**3.2.4.2.1 Exactness of the multi level search** The next reaction  $R_\mu$  in the group  $G_\alpha$  that is selected by the multi-level search has probability  $\frac{a_\mu}{a_0}$ . Let  $\mathbb{P}\{R_\mu\}$  be the probability of selecting the reaction  $R_\mu$ . This can be expanded as:

$$\mathbb{P}\{R_\mu\} = \mathbb{P}\{G_\alpha\}\mathbb{P}\{R_\mu|G_\alpha\} = \frac{a^\alpha}{a_0} \frac{a_\mu}{a^\alpha} = \frac{a_\mu}{a_0}$$

**3.2.4.2.2 Implementation** An implementation to select the group index and the reaction index requires two random numbers:

$$\alpha = \arg \min_{\alpha \in l=1, \dots, L} \sum_{l=1}^{\alpha} a^l \geq r_1 a_0$$

And:

$$\mu = \arg \min_{\mu \in k=1, \dots, M} \sum_{k=1}^{\mu} a_k \geq r_2 a^\alpha$$

$G_\alpha = \{R_j, \dots, R_{j+k_\alpha}\}$

The need for  $r_2$  can be avoided by recycling  $r_1$ :

$$\frac{r_1 a_0 - \sum_{l=1}^{\alpha-1} a^l}{a^\alpha}$$

Is a uniformly distributed random number. SO  $r_1$  is rescaled to select the next reaction firing in the group.

**3.2.4.2.3 Algorithm** The direct method with multi-level search is implemented as in algorithm 6.

### 3.2. DIRECT METHOD

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**Algorithm 6:** Direct method with multi level search()

---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$   

2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$   

3 build the reaction dependency graph  $G$   

4 partition  $M$  reactions into  $L$  groups  $\{G_1, \dots, G_L\}$   

5  $t = 0$   

6  $\vec{X} = \vec{x}_0$   

7 foreach  $G_l$  do  

8    $a^l = 0$   

9   foreach  $R_j \in G_l$  do  

10    compute  $a_j$   

11     $a^l = a^l + a_j$   

12    $a_0 = a_0 + a^l$   

13 while  $t < T_{\max}$  do  

14   generate two random numbers  $r_1, r_2 \sim \text{norm}(0, 1)$   

15   select  $G_\alpha$  with the smallest index  $\alpha$  such that  $\sum_{l=1}^{\alpha} a^l \geq r_1 a_0$   

16    $r_1 = \frac{r_1 a_0 - \sum_{l=1}^{\alpha-1} a^l}{a^\alpha}$   

17   select  $R_\mu$  with the smallest index  $\mu$  such that  $\sum_{k=1}^{\mu} a_k \geq r_1 a^\alpha$   

       $G_\alpha = \{R_j, \dots, R_{j+n}\}$   

18    $\tau = \frac{1}{a_0} \ln \frac{1}{r_2}$   

19    $\vec{X} = \vec{X} + \vec{v}_\mu$   

20    $t = t + \tau$   

21   foreach  $R_j \in \text{Dependents}(R_\mu)$  do  

22    compute  $a_j^{new}$   

23     $a^l = a^l + (a_j^{new} - a_j)$   

24     $a_j = a_j^{new}$ 

```

---

**3.2.4.2.4 Discussion** To analyse the time complexity of the multi-level search assume that  $M$  reactions are partitioned into  $L = \lceil \frac{M}{k} \rceil$  groups and each group contains  $k_l = k$  reactions. The time complexity has two parts:

- Searching for a group  $O\left(\frac{M}{k}\right)$ .
- Searching for a reaction within the group  $O(k)$ .

The total time complexity is then

$$O\left(\frac{M}{k}\right) + O(k) = O(\max\left\{\frac{M}{k}, k\right\})$$

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The total time is minimized by taking  $k = c\sqrt{M}$ , so that the minimal time complexity per reaction event is  $O(\sqrt{M})$ . The multi-level search can be further expanded partitioning the groups into sub-groups, introducing the multi-dimensional search method.

### 3.2.4.3 Direct method with tree-based search

The tree-based search refines the multi-level search. The finest partitioning of reaction is when the lowest level has at most two reaction creating a binary tree structure. Each node has two children or zero and the leaves hold reaction propensity, while internal node hold the sums of the values in their child nodes. The root of the tree holds  $a_0$ .

**3.2.4.3.1 Dimension of a complete tree** A complete binary tree with  $M$  leaves has  $2M - 1$  nodes. Let  $P$  be the number of internal nodes. In a complete tree each internal node has two children, hence the number of edges is  $2P$ . Also the edges are  $M + P - 1$ , so  $P = M - 1$ , so in conclusion the number of nodes is  $P + M = 2M - 1$ .

**3.2.4.3.2 Implementation of the tree** The tree can be implemented by an array with  $2M - 1$  elements. The number of reaction  $M$  has to be even, and if it is not a dummy node with propensity 0 is added to the end of the array. Algorithm 7 outlines how the tree is built: it happens recursively from the leaves to the root, observing that a node in  $i$  will have children in position  $2i$  and  $2i + 1$ .

---

#### Algorithm 7: build\_tree(*position*)

---

- 1 **Input:** an array TREE with  $2M - 1$  elements where elements from  $M$  to  $2M - 1$  are filled with  $M$  reaction propensities and a starting position.
  - 2 **Output:** The complete binary tree represented by the array TREE.
  - 3 **if** *position* <  $M$  **then**
  - 4   **build\_tree**( $2 \cdot \text{position}$ )
  - 5   **build\_tree**( $2 \cdot \text{position} + 1$ )
  - 6    $\text{TREE}[\text{position}] = \text{TREE}[2 \cdot \text{position}] + \text{TREE}[2 \cdot \text{position} + 1]$
- 

**3.2.4.3.3 Tree-based search** The tree-based search for the next reaction firing  $R_\mu$  given  $s = ra_0$  starts by selecting the next branch of the tree by comparing the search value  $s$  with the value stored in the left child of the current node. Then the search selects the left branch if the value is less than the one stored in the left child of the node, otherwise the search chooses the right branch. If the right branch is selected the search value is subtracted by the value stored in the current node. This proceeds recursively until it reaches a leaf and the reaction stored in that leaf is returned with the correct probability  $\frac{a_\mu}{a_0}$ . This procedure is outlined in 8.

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**Algorithm 8:** `search_tree(position, s)`

---

1 **Input:** A complete binary tree represented by the array TREE, and integer position and a search value  $s$   
2 **Output:** The leaf of the complete binary tree which stores the next reaction firing.  
3 **if**  $position \geq$  **then**  
4   **return** position  
5 **else if**  $TREE[2 \cdot position] \geq s$  **then**  
6   **search\_tree**( $2 \cdot position$ ,  $s$ )  
7 **else**  
8    $s = TREE[position] - s$   
9   **search\_tree**( $2 \cdot position + 1$ ,  $s$ )

---

**3.2.4.3.4 Updating the tree** The system is updated after the selected reaction fires. The nodes of the tree will update their propensity value. For each reaction depending on the reaction firing according to the dependency graph  $G$ , its new propensity is computed and the difference is propagated for every of their paths. To optimize this implementation, reactions dependent on each other should be placed as close as possible on the tree. This procedure is outlined in algorithm 9.

---

**Algorithm 9:** `update_tree(position, c)`

---

1 **Input:** A complete binary tree represented by the array TREE.  
2 **Output:** The complete binary tree updated by the reaction firing.  
3  $TREE[position] = TREE[position] + C$   
4 **if**  $position$  is not root **then**  
5   **update\_tree**( $\lfloor \frac{i}{2} \rfloor$ ,  $c$ )

---

**3.2.4.3.5 Algorithm** The whole procedure is implemented in the algorithm 10.

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**Algorithm 10:** Direct method with tree-based search()

---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$   

2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$   

3 build the reaction dependency graph  $G$   

4  $t = 0$   

5  $\vec{X} = \vec{x}_0$   

6 foreach  $R_l$  do  

7   | compute  $a_j$   

8 build TREE structure for  $M$  reaction propensities with 7  

9 while  $t < T_{\max}$  do  

10  | generate two random numbers  $r_1, r_2 \sim \text{norm}(0, 1)$   

11  | select next reaction firing  $R_\mu$  by algorithm 8 with  $s = r_1 a_0$   

12  |  $\tau = \frac{1}{a_0} \ln \frac{1}{r_2}$   

13  |  $\vec{X} = \vec{X} + \vec{v}_\mu$   

14  |  $t = t + \tau$   

15  | foreach  $R_j \in \text{Dependents}(R_\mu)$  do  

16    |   | compute  $a_j^{new}$   

17    |   | update the TREE by algorithm 9 with  $c = a_j^{new} - a_j$   

18    |   |  $a_j = a_j^{new}$ 

```

---

**3.2.4.3.6 Discussion** The search and updated are related to the height of the tree, logarithmic in the number of reactions. So the total computational cost for each reaction event is  $O(\log(M))$ .

**3.2.4.3.7 Tree with optimal height** The computational cost for selecting the next reaction firing in a complete tree is not the optimal average-case performance. Let  $C$  be a tree structure.

**3.2.4.3.7.1 Average number of comparison** The average number of comparison performed during the search in tree  $C$  is:

$$T_m(C) = \sum_{j=1}^M w_j D_j$$

Where:

- $M$  is the total number of reactions in the leaves.
- $w_j$  is a weight related to the probability that reaction  $R_j$  is selected to fire.
- $D_j$  is the depth of leaf  $R_j$ .

**3.2.4.3.7.2 Complete tree** When the tree  $C$  is complete the depth  $D_j$  is the same for all  $j$ . This leads to the fact that picking a fast reaction requires the same computational power of picking a slow one, leading to a non-optimal  $T_M(C)$ .

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**3.2.4.3.7.3 Huffman tree** The minimization of  $T_M(C)$  leads to the construction of the Huffman tree. The leaves in this type of tree with large propensity values will be closer than the leaves with small values. This is built by merging trees in a forest, populated initially by trees with one node. At each step the two trees with roots  $p$  and  $q$  having the smallest weight  $w_p$  and  $w_q$  are merged creating the new root  $pq$  with weight  $w_{pq} = w_p + w_q$ . The process stops when only one tree is found such that  $D_{pq} + 1 = D_q = D$ , where  $p, q, pq$  are the nodes involved in a merge such that:

$$\begin{aligned} T_M(C) &= \sum_{\substack{j=1 \\ j \neq p,q}}^M w_j D_j + w_p D_q = \\ &= \left( \sum_{\substack{j=1 \\ j \neq p,q}}^M w_j D_j + w_{pq} D_{pq} \right) + w_{pq} = \\ &= T_{M-1}(C) + w_{pq} \end{aligned}$$

This derivation allows to determine that the Huffman tree gives the minimum value of  $T_M(C)$ . This is proven by induction on  $M$ . Consider the base case with  $M = 2$ , this is easy to check. By the inductive hypothesis, the Huffman tree for  $M - 1$  gives the optimum value for  $T_{M-1}(C)$ . Suppose by contradiction that the Huffman tree for  $M$  is not optimal, so there is some tree having the total number of comparison  $T'_M(C)$  such that  $T'_M(C) < T_M(C)$ . Without loss of generality the smallest weights are placed at the lowest level. Let  $p$  and  $q$  be the nodes with the smallest weights and label their parent  $pq$ . Using the derivation this gives:

$$T'_{M-1}(C) + w_{pq} < T_{M-1}(C) + w_{pq}$$

Then  $T'_{M-1}(C) < T_{M-1}(C)$ , contradicting the inductive hypothesis.

**3.2.4.3.7.4 Building the Huffman tree** To build a Huffman tree an array with size  $2M - 1$  is considered and each node has two children. However  $M$  does not need to be even. The leaves are between  $M$  and  $2M - 1$ . Each element in the array points to its left and right child and an additional field parent points to the parent of the node. To extract the nodes with minimal weights a binary heap is used, such that each element is  $(i, w_i)$ , where  $i$  is the index of a node in the tree and the weight  $w_i$  is used as the key for ordering the heap. A heap is a tree-based data structure that satisfies the heap property: the key of a parent node is smaller than the key of its child nodes. The implementation for this procedure is presented in algorithm 11

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**Algorithm 11:** build\_huffman\_tree(*position*)

---

```

1 Input: an array TREE with  $2M - 1$  elements where elements from  $M$  to  $2M - 1$  are filled
   with  $M$  reaction propensities
2 Output: The Huffman tree represented by the array TREE.
3 build binary heap  $H$  with elements  $(M, w_1), \dots, (2M - 1, w_M)$  ordered according to  $W_j$ 
4 for position =  $M - 1$  to 1 do
5   extract top element  $(p, w_p)$  from  $H$ 
6   extract top element  $(q, w_q)$  from  $H$ 
7    $TREE[position].VALUE = TREE[p].VALUE + TREE[q].VALUE$ 
8    $TREE[position].LEFT = p$ 
9    $TREE[position].RIGHT = q$ 
10  insert(position,  $w_p + w_q$ ) into  $H$ 
11   $TREE[p].PARENT = position$ 
12   $TREE[q].PARENT = position$ 

```

---

The same binary search and propagation update are applied to search and update the propensities of the reactions.

**3.2.4.3.7.5 Selecting the weight** The weight function  $w_j$  can be the propensity function  $a_j$  because it allows to reduce the time spent to find the next reaction, however reaction firing could make the tree no longer optimal, so it should be rebuilt. To balance the expensive operation of re-building with the non-optimal tree, the non-optimal tree is used for some number of steps. The choice for this step number only affect performance and not exactness. There are two approaches to do so:

- Fixed time tree rebuilding.
- Adaptive time tree rebuilding.

**3.2.4.3.7.6 Fixed time tree rebuilding** In fixed time tree rebuilding the tree structure is built every  $k$  steps. To predict the changes in the reaction propensities during the  $k$  steps the weights can be modified assigning a higher weight to those reaction that are more likely to change.

**Conflicts and Favours set** For a reaction  $R_j$  define:

$$Conflicts(R_j) = \{R_k | (R_j \in Dependents(R_k)) \wedge (Reactants(R_k) \cap Reactants(R_j) \neq \emptyset)\}$$

$$Favors(R_j) = \{R_k | (R_j \in Dependents(R_k)) \wedge (Products(R_k) \cap Reactants(R_j) \neq \emptyset)\}$$

**Dependency graph** In terms of the dependency graph:

$$|Conflicts(R_j)| + |Favors(R_j)| = \text{in degree of } R_j$$

**Estimating changes of propensity** After a reaction firing, the probability that  $R_j$  will increase or decrease is estimated as  $\frac{|Conflicts(R_j)|}{M}$  or  $\frac{|Favors(R_j)|}{M}$ . For  $k$  simulation steps, the estimated weight of reaction  $R_j$  is:

$$w_j(a_j, k) = a_j + \alpha_1 k \frac{|Favors(R_j)|}{M} + \alpha_2 k \frac{|Conflicts(R_j)|}{M}$$

Where  $\alpha_1$  and  $\alpha_2$  are parameters denoting the amount of average change.

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**3.2.4.3.7.7 Adaptive time tree rebuilding** In adaptive time tree rebuilding the tree is rebuilt when a significant change has occurred. To detect the abrupt change in propensities a predefined value  $\delta$ , the acceptance threshold defines the largest change which does not require an immediate tree rebuilding. The difference in propensity after a reaction  $R_j$  firing is  $c_j = a_j^{new} - a_j$ . If  $|c_j| \geq \delta$  the Huffman tree should be rebuilt. To account for many small changes a cumulative sum of all the propensity changes  $s_j$  since the last rebuilt is computed and compared against the acceptance threshold to decide whether to rebuild the tree.

### 3.2.4.4 Direct method with composition-rejection search

The composition-rejection CR search employs the partitioning of reaction into groups, but the selection of the next reaction is performed through an acceptance-rejection sampling. The reactions are partitioned into  $L$  groups so that  $R_j \in G_l$  if  $a_j$  satisfies  $2^{u_{l-1}} \leq a_j \leq 2^{u_l}$  in which  $u_l$  is selected such that  $u_l = \lceil \log_2(a_j) \rceil$ . If  $a_{\min}$  and  $a_{\max}$ , the global minimum and maximum propensities, are known, then  $L = \lceil \log_2 \left( \frac{a_{\max}}{a_{\min}} \right) \rceil$  for the whole simulation. These two bounds on  $a$  can be estimated through physical reasoning. Where this is not possible  $L$  must be increased during the simulation.

**3.2.4.4.1 Search for the next reaction** Let  $a^l = \sum_{R_j \in G_l} a_j$  be the sum of the propensity in group  $G_l$ . The total propensity  $a_0$  can be computed as:

$$a_0 = \sum_{l=1}^L a^l$$

The search is composed of two steps.

**3.2.4.4.1.1 First step** In the first step a group  $G_\alpha$  is selected with probability  $\frac{a^l}{a_0}$ . This can be performed accumulating values  $a^l$  until the smallest index  $\alpha$  is found such that:

$$\sum_{l=1}^{\alpha} a^l \geq r_1 a_0$$

The tree-based search can be applied to select the group.

**3.2.4.4.1.2 Second step** The second step is done through an acceptance-rejection sampling with the chosen envelope  $2^{u_\alpha}$ . A random and uniform reaction index  $\mu \in G_\alpha$  is computed:  $\mu = [r_2 |G_\alpha|]$ , where  $|G_\alpha|$  is the size of  $G_\alpha$  and  $r_2$  is a random number. The selected reaction is tested to accept with probability  $\frac{a_\mu}{2^{u_\alpha}}$ : a random number  $r_3$  is generated and compared against  $\frac{a_\mu}{2^{u_\alpha}}$ .  $r_2$  can be recycled noting that  $r_3 = r_2 |G_\alpha| - \mu$  is uniformly distributed in  $[0, 1]$ . If  $\frac{a_\mu}{2^{u_\alpha}} \leq r_3$  holds,  $R_\mu$  is accepted to fire. Otherwise the reaction is rejected and a new random reaction index is generated and the check is performed again. This is repeated until there is an accepted  $R_\mu$ . The acceptance probability is bound to  $\frac{1}{2}$ :  $\frac{a_\mu}{2^{u_\alpha}} \geq \frac{1}{2}$  by definition.

**3.2.4.4.2 Algorithm** An implementation of this method is found in algorithm 12. The rejection test is repeated on average two times: the acceptance rate is bounded by  $\frac{1}{2}$ . Moreover after a reaction firing the propensity must be updated and it could be that a new reaction falls outside of the current bound, so it must be moved to an appropriate group.

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**Algorithm 12:** Direct Method with Composition-Rejection Search()

---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$   

2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$   

3  $t = 0$   

4  $\vec{X} = \vec{x}_0$   

5 build the dependency graph  $G$   

6 partition  $M$  reactions into  $L$  groups  $\{G_1, \dots, G_L\}$  such that  $R_j \in G_l$  if  $2^{u_l-1} \leq a_j \leq 2^{u_l}$   

7  $a_0 = 0$   

8 foreach  $G_l$  do  

9    $a^l = 0$   

10  foreach  $R_j \in G_l$  do  

11    compute  $a_j$   

12     $a^l = a^l + a_j$   

13   $a_0 = a_0 + a^l$   

14 while  $t < T_{\max}$  do  

15   generate a random number  $r_1 \sim \text{norm}(0, 1)$   

16   select  $G_\alpha$  with the smalles group index  $\alpha$  such that  $\sum_{l=1}^{\alpha} a^l \geq r_1 a_0$   

17   repeat  

18     generate a random number  $r_2 \sim \text{norm}(0, 1)$   

19      $\mu = [r_2 | G_\alpha |]$   

20      $r_2 = r_2 | G_\alpha | - \mu$   

21     until  $r_2 \leq \frac{a_\mu}{2^{u_\alpha}}$   

22     generate a random number  $r_3 \sim \text{norm}(0, 1)$   

23      $\tau = \frac{1}{a_0} \ln \frac{1}{r_2}$   

24      $\vec{X} = \vec{X} + \vec{v}_\mu$   

25      $t = t + \tau$   

26     foreach  $R_j \in \text{Dependents}(R_\mu)$  do  

27       update  $a_j$   

28       if  $a_j \notin [2^{u_l-1}, 2^{u_l}]$  then  

29         move  $R_j$  from  $G_l$  to an appropriate  $G_m$   

30         updated  $a^l$  and  $a^m$   

31       else  

32         update  $a^l$   

33       update  $a_0$ 

```

---

**3.2.4.4.3 Discussion** The selected base 2 in the partition can be chosen arbitrarily, with the dimension of groups and the number of rejections increasing with the base. Moreover efficient data structures are needed to implement the movement of reactions between groups: this should support dynamic memory allocation operation. In addition a hash table should be used to support fast lookup of a reaction in a group. For adding a reaction to a group, the group size is increased and

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the reaction is added at the end of the group. When deleting a reaction, the reaction at the end of the group replaces it and the group size is decremented. After each of this two operations, the hash table is updated.

**3.2.4.4.3.1 Computational cost** The computational cost is composed by the search for the group, proportional to the number of groups  $O(L)$  and the cost for selecting the next reaction, which is constant. Because the average number of rejection tests is bound by 2, the time is  $O(L)$  and is independent of the number of reactions  $M$ . If  $L \ll M$  and is bounded by a small constant the search for the next reaction firing is  $O(1)$ .

### 3.2.5 Partial-propensity direct method

The partial propensity direct method PDM requires that reactions must be elementary and their propensities follow the mass action kinetics. Mass action propensities are factorized and the partial propensities related to common reactants are grouped to facilitate the selection of the next reaction firing. Let  $\pi_j^i$  the partial propensity of a reaction  $R_j$  with respect to reactant  $S_i$ , this is defined as the propensity per molecule of reactant  $S_i$ .

#### 3.2.5.1 Partial propensities of elementary reactions

- Synthesis reaction ( $\emptyset \rightarrow$  products): propensity  $a_j = c_j$  and partial propensity  $\pi_j^0 = c_j$ .
- Unimolecular reaction ( $S_i \rightarrow$  products): propensity  $a_j = c_j X_i$  and partial propensity  $\pi_j^i = c_j$ .
- Bimolecular reaction ( $S_i + S_k \rightarrow$  products): propensity  $a_j = c_j X_i X_k$  and partial propensity  $\pi_j^i = c_j X_k$  and  $\pi_j^{(k)} = c_j X_i$ .
- Dimerization reaction ( $2S_i \rightarrow$  products): propensity  $a_j = \frac{1}{2} c_j X_i (X_i - 1)$  and partial propensity  $\pi_j^i = \frac{1}{2} c_j (X_i - 1)$ .

#### 3.2.5.2 Storing the partial propensities

The partial propensities related to a species  $S_i$  are grouped into a group  $\Pi_i$ , such that the structure:

$$\Pi = \{\Pi_i\}_{i=0}^N$$

Stores all of them and is a matrix implemented as an array of arrays. It has  $N + 1$  rows in which the  $i$ -th row stores the partial propensities related to species  $S_i$ , while the 0-th row stores all the partial propensities for synthesis reactions. In the case of a bimolecular reaction one of the two partial propensities has to be dropped.

**3.2.5.2.1 Minimizing updates** To minimize updates the partial propensities are stored with respect to the reactant involved in a larger number of reaction: before building  $\Pi$ , the species are re-indexed such that for each pair of them  $S_i$  and  $S_k$ ,  $i < k$  if the number of reactions involving  $S_i$  is greater than  $S_k$ . Then PDM stores partial propensity of a bimolecular reaction with respect to the reactant with smaller index.

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### 3.2.5.3 Group-sum array

The sum  $\Lambda_i = \sum_j \Pi_{i,j}$  gives the sum of partial propensities of reactions  $R_j$  sharing common reactant  $S_i$ . This is the group-sum array and is used to store the sum of partial propensities in group.  $\Omega_i = X_i \Lambda_i$ , where  $X_i$  is the population of  $S_i$  will be the sum of propensities of reaction having species  $S_i$  as the common reactant. The array  $\Omega = \{\Omega_i\}_{i=0}^N$  to store the sum of propensities of gropus. The total propensity is computed as:

$$a_0 = \sum_{i=0}^N \Omega_i$$

### 3.2.5.4 Reaction lookup

A reaction is identified by the group index  $i$  and the element  $j$  in a group  $\Pi_i$ . To facilitate the lookup of a reaction given the element  $j$ , a lookup table  $\mathbf{L}$  is used to store the reaction indices of corresponding partial propensities in  $\Pi$ . It has the same structure as  $\Pi$  and is implemented as an array of arrays. The index of reaction with element index  $j$  in group  $i$  of  $\Pi$  is identified as  $\mathbf{L}_{ij}$ , moreover three additional lookup table are used to facilitate the update of  $\Pi$ ,  $\Lambda$  and  $\Omega$  after a reaction firing:

- $\mathbf{U}^{(1)}$  is an array of  $M$  arrays in which array  $j$  contains the indices of species involved in  $R_j$ .
- $\mathbf{U}^{(2)}$  is an array of  $M$  arrays in which the array  $j$  contains the amount of change in population of the corresponding species in  $\mathbf{U}^{(1)}$ .
- $\mathbf{U}^{(3)}$  is an array of  $N$  arrays in which array  $k$  contains pairs of group indices and element indices of all entry in  $\Pi$  that depend on species  $k$ . Each element in the row  $k$  is a pair denoting the partial propensity  $\Pi_{i,j}$  dependent in  $X_k$ .

### 3.2.5.5 Selecting the reaction firing

PDM selects  $R_\mu$  in two steps. Let  $r_1$  b a uniformly distributed random number in  $norm(0, 1)$ .

#### 3.2.5.5.1 First step

Search for the group index  $p$ , with  $0 \leq p \leq N$ :

$$p = \arg \min_{i \in p} \sum_{i=0}^p \Omega_i \geq r_1 a_0$$

#### 3.2.5.5.2 Second step

Search for an element index  $q$ , with  $q \geq 1$  such that:

$$q = \arg \min_{i \in q} \left( X_p \sum_{j=1}^q \Pi_{p,j} + \sum_{i=0}^p \Omega_i - \Omega_p \right) \geq r_1 a_0$$

Or:

$$q = \arg \min_{i \in q} \Pi_{o,j} \geq \Psi$$

Where:

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$$\Psi = \frac{r_1 a_0 - \sum_{i=0}^p \Omega_i + \Omega_p}{X_p}$$

Then  $p$  and  $q$  are used to retrieve the reaction firing index  $\mu = \mathbf{L}_{p,q}$ .

#### 3.2.5.6 Exactness of PDM

The next reaction firing  $R_\mu$  is selected by PDM having probability  $\frac{a_\mu}{a_0}$ . The selection of the reaction is performed by DM as:

$$\mu = \arg \min_{\mu \in j} \sum_{j=1}^{\mu} s_j \geq r_1 a_0$$

PDM identifies a reaction by a pair  $(p, q)$  where  $p$  is the group index and  $q$  the element index in  $\Pi$  by  $\mu = \mathbf{L}_{p,q}$ , then the equation can be re-written as:

$$(p, q) = \arg \min_{p \in i \wedge q \in j} \sum_{i=0}^p \sum_j a_{\mathbf{L}_{p,j}} \geq r_1 a_0$$

That can be broken down in:

$$p = \arg \min_{p \in i} \sum_{i=0}^p \sum_j a_{\mathbf{L}_{i,j}} \geq r_1 a_0$$

$$q = \arg \min_{q \in j} \sum_{i=0}^p \sum_j a_{\mathbf{L}_{i,j}} + \sum_{j=1}^q a_{\mathbf{L}_{p,j}} \geq r_1 a_0$$

Plugging into this two the definitions of  $\Omega$  and  $\Pi$  they are equivalent to the one for the PDM seen before.

#### 3.2.5.7 Algorithm

PDM is implemented as in algorithm 13.

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**Algorithm 13:** Partial-Propensity Direct Method (PDM)()

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**1 Input:** a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$  with mass action kinetics  
**2 Output:** a trajectory of the biochemical reaction network, which is a collection of states  $X(t)$  for time  $0 \leq t \leq T_{\max}$   
**3**  $t = 0$   
**4**  $\vec{X} = \vec{x}_0$   
**5** build  $\Pi$ ,  $\Lambda$ ,  $\Omega$  and  $\mathbf{L}$ ,  $\mathbf{U}^{(1)}$ ,  $\mathbf{U}^{(2)}$  and  $\mathbf{U}^{(3)}$   
**6**  $a_0 = 0$   
**7 foreach**  $i \in \Omega$  **do**  
**8**    $a_0 = a_0 + \Omega_i$   
**9 while**  $t < T_{\max}$  **do**  
**10**   generate two random numbers  $r_1, r_2 \sim \text{norm}(0, 1)$   
**11**   select the smallest group index  $p$  such that  $\sum_{i=0}^p \Omega_i \geq r_1 a_0$   
**12**    $\Psi = \frac{r_1 a_0 - \sum_{i=0}^p \Omega_i + \Omega_p}{X_p}$   
**13**   select  $R_\mu$  with the smallest index  $q$  such that  $\sum_{j=1}^q \Pi_{p,j} \geq \Psi$   
**14**    $\mu = \mathbf{L}_{p,q}$   
**15**    $\tau = \frac{1}{a_0} \ln \frac{1}{r_2}$   
**16**    $\Delta a = 0$   
**17 foreach**  $k \in \mathbf{U}_\mu^{(1)}$  **do**  
**18**     $l = \mathbf{U}_{\mu,k}^{(1)}$   
**19**     $X_l = X_l + \mathbf{U}_{\mu,k}^{(2)}$   
**20 foreach**  $m \in \mathbf{U}_l^{(3)}$  **do**  
**21**       $(i, j) = \mathbf{U}_{l,m}^{(3)}$   
**22**       $\mu' = \mathbf{L}_{i,j}$   
**23**      **if**  $l \neq i$  **then**  
**24**         $\Pi_{i,j} = \Pi_{i,j} + c_{\mu'} \mathbf{U}_{\mu,k}^{(2)}$   
**25**         $\Lambda_i = \Lambda_i + c_{\mu'} \mathbf{U}_{\mu,k}^{(2)}$   
**26**      **else if**  $l = i$  **then**  
**27**         $\Pi_{i,j} = \Pi_{i,j} + \frac{1}{2} c_{\mu'} \mathbf{U}_{\mu,k}^{(2)}$   
**28**         $\Lambda_i = \Lambda_i + \frac{1}{2} c_{\mu'} \mathbf{U}_{\mu,k}^{(2)}$   
**29**       $\Omega_{temp} = \Omega_i$   
**30**       $\Omega_i = X_i \Lambda_i$   
**31**       $\Delta a = \delta a + \Omega_i - \Omega_{temp}$   
**32**       $\Delta a = \Delta a + X_k \Lambda_l - \Omega_l$   
**33**       $\Omega_l = X_l \Lambda_l$   
**34**     $a_0 = a_0 + \Delta a$   
**35**     $t = t + \tau$

---

## 3.2. DIRECT METHOD

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### 3.2.5.7.1 Discussion

**3.2.5.7.1.1 Time complexity** The time complexity of the search for the next reaction firing has two parts:

- Selecting the group, which in the worst case travels  $N + 1$  groups, in time  $O(N)$ .
- Selecting the element in the group, which is proportional to the number of reactions

sharing the same reactant. This is model dependent and bounded by a small constant. For elementary reactions the worst case is  $N$ , so the cost for this step is  $O(N)$ .

In total the time complexity for the search for the next reaction firing in PDM is  $O(N)$ .

**3.2.5.7.1.2 Limitations** The major limitation of PDM is that it works for a class of reactions involving at most two reactants with factorisable reaction propensities. For models with high-order reactions the propensity is not factorizable and they must be broken down into elementary reactions and the propensity computation has to be modified.

### 3.2.5.8 Partial propensity direct method with composition-rejection search

The partial propensity direct method with composition-rejection search PDM-CR is a variant of PDM where the selection of  $p$  and  $q$  are done through the composition-rejection approach. ‘ $M$ ’ is grouped into  $L$  groups such that  $G_l$  stores group index  $i$  such that  $2^{u_l-1} \leq \Omega_i < 2^{u_l}$  with  $u_l = \lceil \log_2(\Omega_i) \rceil$ . The sum of propensities in  $G_l$  is:

$$a^l = \sum_{i \in G_l} \Omega_i$$

For  $\Pi$  each  $i$  row is partitioned into  $K_i$  groups such that  $Q_k^i$  stores element index  $j$  such that  $2^{v_k^i-1} \leq \Pi_{i,j} < 2^{v_k^i}$  with  $v_k^i = \lceil \log_2(\Pi_{i,j}) \rceil$ . The sum of partial propensity in  $Q_k^i$  is:

$$b_i^k = \sum_{j \in Q_k^i} \Pi_{i,j}$$

For each row of  $\Pi$  the relation  $\sum_{k=1}^{K_i} b_i^k = \sum_j \Pi_{i,j} = \Lambda_i$  holds.

**3.2.5.8.1 Selection of the next reaction firing** The selection of the next  $R_\mu$  consists of two CR searches: the first selects the group index  $p$  and the second the element index  $q$ .

**3.2.5.8.1.1 Selecting group index** To select the group index  $p$  two random numbers  $r_1, r_2 \sim \text{norm}(0, 1)$  are sampled. Then a group  $G_\alpha$  is selected with probability  $\frac{a^\alpha}{a_0}$  with  $a_0 = \sum_{l=1}^L a^l = \sum_{i=0}^N \Omega_i$  accumulating  $a^l$  until the smallest  $\alpha$  is found such that:

$$\sum l = 1^\alpha a^l \geq r_1 a_0$$

Then  $r_2$  is used to accept the group index  $p$  in  $G_\alpha$  through an acceptance-rejection test with probability  $\frac{\Omega_p}{2^{u_\alpha}}$ .

### 3.2. DIRECT METHOD

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**3.2.5.8.1.2 Selecting element index** Once  $p$  has been selected  $q$  is selected through a second CR search. This requires two random numbers  $r_3, r_4 \sim \text{norm}(0, 1)$ . A group  $Q_\beta^p$  is selected with probability  $\frac{b_p^\beta}{\Lambda_p}$  by a linear search. Then the element index  $q$  in the groups is selected through an acceptance-rejection test with probability  $\frac{\Pi_{p,q}}{2^{v_p^\beta}}$ .

**3.2.5.8.2 Algorithm** The PDM-CR implementation is outlined in algorithm 14

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**Algorithm 14:** Partial-Propensity Direct Method with Composition-Rejection Search (PDM-CR)()

---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

 $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$  with mass action kinetics
2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

 $X(t)$  for time  $0 \leq t \leq T_{\max}$ 
3  $t = 0$ 
4  $\vec{X} = \vec{x}_0$ 
5 build  $\Pi$ ,  $\Lambda$ ,  $\Omega$  and  $\mathbf{L}$ ,  $\mathbf{U}^{(1)}$ ,  $\mathbf{U}^{(2)}$  and  $\mathbf{U}^{(3)}$ 
6 partition  $\Omega$  into  $L$  groups  $G_1, \dots, G_L$  such that  $G_l$  contains  $\Omega_l$  if  $2^{u_l-1} \leq \Omega_i < 2^{u_l}$ 
7  $a_0 = 0$ 
8 foreach  $G_l \in \{G_1, \dots, G_L\}$  do
9    $a^l = \sum_{i \in G_l} \Omega_i$ 
10   $a_0 = a_0 + a^l$ 
11 for  $i = 0 \Rightarrow N$  do
12   partition  $\Pi_i$  into  $K_i$  groups  $Q_1^i, \dots, Q_{K_i}^i$  such that  $Q_k^i$  contains  $\Pi_{i,j}$  if  $2^{v_k^i-1} \leq \Pi_{i,j} < 2^{v_k^i}$ 
13   for  $i = 1 \rightarrow K_i$  do
14      $b_i^k = \sum_{\Pi_{i,j} \in Q_k^i} \Pi_{i,j}$ 
15 while  $t < T_{\max}$  do
16   generate a random number  $r_1 \sim \text{norm}(0, 1)$ 
17   select the smallest group  $G_\alpha$  such that  $\sum_{l=1}^{\alpha} a^l \geq r_1 a_0$ 
18    $\Psi = \frac{r_1 a_0 - \sum_{i=0}^p \Omega_i + \Omega_p}{X_p}$ 
19   select  $R_\mu$  with the smallest index  $q$  such that  $\sum_{j=1}^q \Pi_{p,j} \geq \Psi$ 
20 repeat
21   generate a random number  $r_2 \sim \text{norm}(0, 1)$ 
22    $p = [r_2 |G_\alpha|]$ 
23    $r_2 = r_2 |G_\alpha| - p$ 
24 until  $r_2 < \frac{\Omega_p}{2^{u_\alpha}}$ 
25 generate a random number  $r_3 \sim \text{norm}(0, 1)$ 
26 select the smallest group  $Q_\beta^p$  such that  $\sum_{k=1}^{\beta} b_p^k \geq r_3 \Lambda_p$ 
```

---

### 3.3. FIRST REACTION METHOD

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```

1 Contd-While
2   repeat
3     generate a random number  $r_4 \sim \text{norm}(0, 1)$ ;
4      $q = [r_4|Q_\beta^p]|$ ;
5      $r_4 = r_4|Q_\beta^p| - q$ ;
6     until  $r_4 < \frac{\Pi_{p,q}}{2^{v_\beta}}$ ;
7      $\mu = \mathbf{L}_{p,q}$ ;
8      $\tau = \frac{1}{a_0} \ln \frac{1}{r_2}$ ;
9      $\Delta a = 0$ ;
10    foreach  $k \in \mathbf{U}_\mu^{(1)}$  do
11       $l = \mathbf{U}_{\mu,k}^{(1)}$ ;
12       $X_l = X_l + \mathbf{U}_{\mu,k}^{(2)}$ ;
13      foreach  $m \in \mathbf{U}_l^{(3)}$  do
14         $(i, j) = \mathbf{U}_{l,m}^{(3)}$ ;
15         $\mu' = \mathbf{L}_{i,j}$ ;
16        if  $l \neq i$  then
17           $\Pi_{i,j} = \Pi_{i,j} + c_{\mu'} \mathbf{U}_{\mu,k}^{(2)}$ ;
18           $\Lambda_i = \Lambda_i + c_{\mu'} \mathbf{U}_{\mu,k}^{(2)}$ ;
19        else if  $l = i$  then
20           $\Pi_{i,j} = \Pi_{i,j} + \frac{1}{2} c_{\mu'} \mathbf{U}_{\mu,k}^{(2)}$ ;
21           $\Lambda_i = \Lambda_i + \frac{1}{2} c_{\mu'} \mathbf{U}_{\mu,k}^{(2)}$ ;
22         $\Omega_{temp} = \Omega_i$ ;
23         $\Omega_i = X_i \Lambda_i$ ;
24         $\Delta a = \delta a + \Omega_i - \Omega_{temp}$ ;
25        updated group  $G_i$  and  $Q_j^i$ ;
26         $\Delta a = \Delta a + X_k \Lambda_l - \Omega_l$ ;
27         $\Omega_l = X_l \Lambda_l$ ;
28      updated group  $G_l$ ;
29       $a_0 = a_0 + \Delta a$ ;
30       $t = t + \tau$ ;

```

---

## 3.3 First reaction method

The first reaction method FRM is an alternative method to implement the Monte Carlo step of SSA. The next reaction firing  $R_\mu$  and firing time  $\tau$  are exact, so they are ensured to be distributed by the pdf  $p(\tau, \mu | \vec{x}, t)$ .

### 3.3.1 Tentative time

In FRM the reaction selected to fire is the one with the smallest tentative time. The tentative time is the firing time of the reaction assuming that no other reaction fires before. Let  $\tau_j$  be the tentative

### 3.3. FIRST REACTION METHOD

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time to the firing of  $R_j$  assuming that no other reaction fires before. Let  $p(\tau_j|\vec{x}, t)$  be the pdf of  $\tau_j$  such that  $p(\tau_j|\vec{x}, t)d\tau_j$  gives the probability that  $R_j$  fires in the next infinitesimal time interval  $[t + \tau_j, t + \tau_j + d\tau_j[$  assuming that no other reaction fires before. The formula of  $p(\tau_j|\vec{x}, t)$ , noting that there is only one  $R_j$  involved in the calculation is:

$$p(\tau_j|\vec{x}, t) = a_j e^{-a_j \tau_j}$$

From this the tentative time can be generated applying the inverse transforming method:

$$\tau_j = \frac{1}{a_j} \ln \left( \frac{1}{r_j} \right)$$

Where  $r_j \sim \text{norm}(0, 1)$ .

#### 3.3.2 Exactness of the first reaction method

Let  $R_\mu$  be the reaction having the smallest tentative time  $\tau = \min_{j=1}^M \{\tau_j\}$  where each  $\tau_j$  with  $j = 1, \dots, M$  is distributed according to the pdf  $p(\tau_j|\vec{x}, t) = a_j e^{-a_j \tau_j}$ . Let  $\tilde{p}(\tau, \mu|\vec{x}, t)d\tau$  be the probability that  $R_\mu$  fires at time  $\tau$ , then:

$$\tilde{p}(\tau, \mu|\vec{x}, t) = a_\mu e^{-a_\mu \tau}$$

The probability of  $R_\mu$  which has the smallest time  $\tau = \min_{j=1}^M \{\tau_j\}$  to fire at time  $\tau$  is:

$$\tilde{p}(\tau, \mu|\vec{x}, t)d\tau = \mathbb{P}\{\tau < \tau_\mu < \tau + d\tau\} \mathbb{P}\{\tau_j > \tau \forall j \neq \mu\}$$

Where:

- $\mathbb{P}\{\tau < \tau_\mu < \tau + d\tau\}$  is the probability that  $R_\mu$  with smallest tentative fire  $\tau_\mu$  fires in  $[\tau, \tau + d\tau[$ .
- $\mathbb{P}\{\tau_j > \tau \forall j \neq \mu\}$  is the probability that  $\tau_j$  of  $R_j$  is greater than  $\tau$ .

The first probability is directly derived from the definition of  $\tau_\mu$  as:

$$\mathbb{P}\{\tau < \tau_\mu < \tau + d\tau\} = a_\mu e^{-a_\mu \tau} d\tau$$

The second one is derived as follows:

$$\begin{aligned} \mathbb{P}\{\tau_j < \tau \forall j \neq \mu\} &= \mathbb{P}\left\{ \frac{1}{a_j} \ln \left( \frac{1}{r_j} \right) \forall i \neq \mu \right\} = \\ &= \mathbb{P}\{r_j < e^{-a_j \tau} \forall j \neq \mu\} = \\ &= \prod_{i=1 \wedge i \neq \mu}^M \mathbb{P}\{r_j < e^{-a_j \tau}\} = \\ &= \prod_{i=1 \wedge i \neq \mu}^M e^{-a_j \tau} \end{aligned}$$

### 3.3. FIRST REACTION METHOD

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In which the generation of  $\tau_j$  is considered, and the third step follows from the fact that  $r_j$ s are all independent and identically distributed random numbers. The last holds because the probability that a uniformly distribute random number from a unit interval is less than a number is equal to that number. Now, plugging the last to into  $\tilde{p}$  and recalling the definition of total propensity, the probability distribution of the next reaction firing is:

$$\tilde{p}(\tau, \mu | \vec{x}, t) = a_\mu e^{-a_\mu \tau} \left( \prod_{j=1 \wedge j \neq \mu} e^{-a_j \tau} \right) = a_\mu e^{-a_0 \tau}$$

#### 3.3.3 Algorithm

An implementation of the steps of FRM is presented in algorithm 15. For each simulation iteration  $M$  uniformly distributed random numbers  $r_j$  are generated and used to compute the tentative time  $\tau_j$  for all reactions. Then the reaction with the smallest time is selected to fire. Once the reaction has fired, the time and state are updated accordingly.

---

**Algorithm 15:** First Reaction Method (FRM) ()

---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$ 
2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$ 
3  $t = 0$ 
4  $\vec{X} = \vec{x}_0$ 
5 while  $t < T_{\max}$  do
6   foreach  $R_j$  do
7     compute  $a_j$ 
8     generate a random number  $r_j \sim \text{norm}(0, 1)$ 
9      $\tau_j = \frac{1}{a_j} \ln \left( \frac{1}{r_j} \right)$ 
10    select  $R_\mu$  with the smallest tentative time  $\tau = \min_{j=1}^M \{\tau_j\}$ 
11     $\vec{X} = \vec{X} + \vec{v}_\mu$ 
12     $t = t + \tau$ 

```

---

##### 3.3.3.1 Time complexity

The time complexity is due to:

- Computing the tentative time of reactions.  
This, for  $M$  reaction, is done in  $O(M)$  time.
- Searching for the reaction with the small-  
est tentative time. This is also  $O(M)$  as  
they can be linearly compared as they are  
generated.

The time complexity is thus  $O(M)$  for a time step and this algorithm is easy to parallelize. However it is often slower than DM because a large number of random numbers are required at each iterations. FRM is therefore slower than DM if the number of reactions  $M \geq 2$ .

### 3.3. FIRST REACTION METHOD

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#### 3.3.4 First family method

The first family method FFM is a generalization of DM and FRM methods. It partitions  $M$  reactions into  $L$  families. Each  $F_l$  contains  $k_l$  reactions, that can be different between families.  $L$  and  $k_l$  are tunable parameters. Note that because the partition is complete  $\sum_{l=1}^L k_l = M$ .

##### 3.3.4.1 Next reaction event

The next reaction event in FFM is a pair  $(\alpha, \mu)$  denoting  $R_\mu$  in family  $F_\alpha$ . The selection is performed in two steps:

- Selection of the family.
- Selection of the reaction.

**3.3.4.1.1 Selection of the family** The selection is performed in two steps: a family with the smallest tentative time is selected. The tentative time of  $F_l$  is generated from an exponential distribution with rate equal to the sum of reaction propensities in the family. Let  $a^l = \sum_{R_j \in F_l} a_j$  be the sum of propensities, then the tentative time will be computed as:

$$\tau_l = \frac{1}{a^l} \ln \left( \frac{1}{r_l} \right)$$

Where  $r_l \sim \text{norm}(0, 1)$ .

**3.3.4.1.2 Selection of the reaction** Let  $F_\alpha$  be the family with the smallest tentative time:  $\tau = \min_{l=1}^L \{\tau_l\}$ . Conditioning on the selected  $F_\alpha$ ,  $R_\mu$  is selected with probability  $\frac{a_\mu}{a^\alpha}$ . A DM search is applied to find the next reaction:

$$\mu = \arg \min_{k \in F_\alpha} \sum_{\substack{k=j \\ F_\alpha = \{R_j, \dots, R_{j+k\alpha}\}}}^{\mu} a_k \geq r a^\alpha$$

Where  $r \sim \text{norm}(0, 1)$ .

#### 3.3.4.2 Algorithm

An implementation of the FFM is presented in algorithm 16. For each simulation step,  $L$  random number are required to compute the tentative times and an additional one is used to select the next reaction firing.

### 3.4. NEXT REACTION METHOD

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**Algorithm 16: First Family Method (FFM) ()**


---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$   

2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$   

3  $t = 0$   

4  $\vec{X} = \vec{x}_0$   

5 partition  $M$  reactions into  $L$  families  $\{F_1, \dots, F_L\}$   

6 while  $t < T_{\max}$  do  

7   foreach  $F_l$  do  

8      $a^l = 0$   

9     foreach  $R_j$  do  

10       compute  $a_j$   

11        $a^l = a^l + a_j$   

12       generate a random number  $r_l \sim \text{norm}(0, 1)$   

13        $\tau_l = \frac{1}{a^l} \ln \left( \frac{1}{r_l} \right)$   

14     select  $F_\alpha$  with smallest tentative time  $\tau = \min_{l=1}^L \{\tau_l\}$   

15     generate a random number  $r \sim \text{norm}(0, 1)$   

16     select  $R_\mu \in F_\alpha$  with the smallest index  $\mu$  such that  $\sum_{k=j}^{\mu} a_k \geq r a^\alpha$   

17      $\vec{X} = \vec{X} + \vec{v}_\mu$   

18      $t = t + \tau$ 

```

---

#### 3.3.4.2.1 Discussion

**3.3.4.2.1.1 Performance** It can be seen how  $L + 1$  random number are generated by FFM, so it has better performance than FRM when the number of reactions  $M \gg L$  thanks to the smaller number of random number generation. This algorithm is still parallelizable for the families.

**3.3.4.2.1.2 Comparison with DM and FRM** DM and FRM are special cases of FFM obtained by tuning  $L$  and  $k_l$ . If  $L = 1$  the algorithm is reduced to the DM. If  $L = M$  and  $k_l = 1$  the algorithm reduces to FRM. Great attention has to be posed to the propensity of the families: if one is much greater than the other the algorithm could choose only that family.

## 3.4 Next reaction method

The next reaction method NRM improves FRM:

- Avoids recomputing propensities of all reaction after a firing. It recomputes the propensity  $a_j$  of  $R_j$  only if it actually changes extracting them from a reaction dependency graph  $G$ .

### 3.4. NEXT REACTION METHOD

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- Switches to absolute tentative time instead of relative and reuses the time when appropriate. For each simulation step it generates the new time for the reaction firing, while the other are updated and reused, reducing the number of random number used in the simulation.
- it employs efficient data structures to store and retrieve putative firing time of reaction, making the selection of the next reaction fast and efficient.

#### 3.4.1 Absolute tentative time

Let  $\tau_j$  be the tentative time to the firing of  $R_j$  with pdf  $p(\tau_j | \text{vec}x, t) = a_j e^{-a_j \tau_j}$ . Let  $\tau_m = \min_{k=1}^M \tau_j$ . The residual  $\tau_j - \tau_m$  is transformed for all  $j \neq \mu$  to compute the new tentative time for  $R_j$ .

##### 3.4.1.1 Distribution of the residual time

$\tau_j - \tau_\mu$  is exponentially distributed with rate  $a_j$ : let  $X$  be a random variable with an exponential density function:

$$f(x) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & x < 0 \end{cases}$$

Where  $\lambda > 0$  is a parameter, then,  $\forall s > t \geq 0$ :

$$\mathbb{P}\{X > s | X > t\} = \mathbb{P}\{X > s - t\}$$

Expanding the left-hand side:

$$\begin{aligned} \mathbb{P}\{X > s | X > t\} &= \frac{\mathbb{P}\{X > s \wedge X > t\}}{\mathbb{P}\{X > t\}} = \frac{\mathbb{P}\{X > s\}}{\mathbb{P}\{X > t\}} = \frac{1 - \mathbb{P}\{X \leq s\}}{1 - \mathbb{P}\{X \leq t\}} = \\ &= \frac{1 - \int_{-\infty}^s f(x) dx}{1 - \int_{-\infty}^t f(x) dx} = \frac{1 - \int_0^s \lambda e^{-\lambda x} dx}{1 - \int_0^t \lambda e^{-\lambda x} dx} = \frac{e^{-\lambda s}}{e^{-\lambda t}} = \\ &= e^{-\lambda(s-t)} \end{aligned}$$

And the right-hand side:

$$\begin{aligned} \mathbb{P}\{X > s - t\} &= 1 - \mathbb{P}\{X \leq s - t\} = 1 - \int_{-\infty}^{s-t} f(x) dx = \\ &= 1 - \int_0^{s-t} \lambda e^{-\lambda x} dx = e^{-\lambda(s-t)} \end{aligned}$$

Obtaining the required equality.

##### 3.4.1.2 Relationship between absolute and relative tentative time

Let  $t_j$  the absolute tentative time: the time from the start of the simulation to the firing of  $R_j$ . The relationship between the absolute and tentative time is:

$$t_j = t + \tau + j$$

### 3.4. NEXT REACTION METHOD

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Where  $t$  is the current simulation time. The reaction with the smallest absolute time is the reaction with the smallest relative time because  $t$  is fixed. However using it NRM does not need the random number necessary to generate the new tentative times.

#### 3.4.1.3 Computing the absolute time

Let  $R_\mu$  the reaction with smallest  $t_\mu$ . After it fires and  $t$  is advanced to  $t_\mu$ , the new times for reactions have to be generated. For  $R_\mu$  a new tentative time is generated from an exponential distribution  $t_\mu^{new} = e^{a_\mu^{new}}$  and the absolute time is updated to:

$$t_\mu^{new} + t_\mu + \tau_\mu^{new}$$

For each  $R_j$  with  $j \neq \mu$ , let  $a_j^{new}$  and  $\tau_j^{new}$  be the new propensity value and new relative time. In the case that  $R_j$  does not depend on  $R_\mu$  and the propensity of the reaction does not change by firing, the difference  $\tau_j - \tau_m = t_j - t_\mu$  can be used as the new relative tentative time  $\tau_j^{new}$  of the reaction, so that the absolute time does not change:

$$t_j^{new} = \tau_j^{new} + t_\mu = t_j - t_\mu + t_\mu = t_j$$

If  $R_j \in Depenents(R_\mu)$  and  $j \neq \mu$ , the propensity  $a_j$  changes to  $a_j^{new}$ . A new relative tentative time, an exponential random number with rate  $a_j^{new}$  has to be computed.

**3.4.1.3.1 Computing the new tentative time** Let  $X$  be a random variable with exponential density function:

$$f_X(x) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & x < 0 \end{cases}$$

Where  $\lambda > 0$  is a parameter. Let  $Y$  be a random variable such that  $Y = cX$ , where  $c > 0$  is a constant, then the probability density function of  $Y$  is:

$$f_Y(x) = \begin{cases} \frac{\lambda}{c} e^{-\frac{\lambda}{c}x} & x \geq 0 \\ 0 & x < 0 \end{cases}$$

Let  $F_Y(x)$  be the cdf of  $Y$ , then:

$$\begin{aligned} f_Y(x) &= \frac{dF_Y(x)}{dx} = \frac{d\mathbb{P}\{Y \leq x\}}{dx} = \frac{d\mathbb{P}\{cX \leq x\}}{dx} = \frac{d\mathbb{P}\{X \leq \frac{x}{c}\}}{dx} = \\ &= \frac{d\left(\int_{-\infty}^{\frac{x}{c}} f_X(s)ds\right)}{dx} \end{aligned}$$

If  $x < 0$ , then  $f_Y(x) = 0$ . If  $x \geq 0$ :

$$\begin{aligned} f_Y(x) &= \frac{d\left(\int_0^{\frac{x}{c}} \lambda e^{-\lambda s} ds\right)}{dx} = \frac{d\left(1 - e^{-\frac{\lambda}{c}x}\right)}{dx} = \\ &= \frac{\lambda}{c} e^{-\frac{\lambda}{c}x} \end{aligned}$$

### 3.4. NEXT REACTION METHOD

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This ensures that:

$$\tau_j^{new} = \frac{a_j}{a_j^{new}}(t_j - t_\mu)$$

Is exponentially distributed with rate  $a_j^{new}$  as desired, so the new value for the absolute tentative time for  $R_j$  is:

$$t_j^{new} = \tau_j^{new} + t_\mu = \frac{a_j}{a_j^{new}}(t_j - t_\mu) + t_\mu$$

#### 3.4.1.4 Conclusion

In conclusion NRM does not generate new random numbers to compute the new times for all the reactions: the old time is reused to compute the new one.

#### 3.4.2 Data structures

To speed up the selection of the minimum  $t_\mu$ , NRM employs a binary heap to index the absolute putative times  $t_j$  of reactions  $R_j$ . Each node is a pair  $(t_j, R_j)$  in which  $t_j$  is a key that prioritize the node. It maintains a partial order between nodes: the parent have a smaller time than its child. The selection of the reaction with smallest time is constant: it is on the top of the heap. The heap has to be updated for each reaction whose time is changed. To do this the node containing the reaction is updated with the new time and is swept up and down to maintaining the order of the heap. This costs  $O(\log(M))$ .

#### 3.4.3 Algorithm

An implementation of the next reaction method is presented in algorithm 17.

### 3.4. NEXT REACTION METHOD

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**Algorithm 17:** Next Reaction Method (NRM) ()

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```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$ 
2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$ 
3  $t = 0$ 
4  $\vec{X} = \vec{x}_0$ 
5 build the reaction dependency graph  $G$ 
6 foreach  $R_j$  do
7   compute  $a_j$ 
8   generate a random number  $r_j \sim \text{norm}(0, 1)$ 
9    $t_j = \frac{1}{a_j} \ln \left( \frac{1}{r_j} \right)$ 
10 build the binary heap  $H$  for  $M$  tentative times  $t_j$ 
11 while  $t < T_{\max}$  do
12   extract the node with smallest  $t_\mu$  and reaction  $R_\mu$  from  $H$ 
13    $t = t_\mu$ 
14    $\vec{X} = \vec{X} + \vec{v}_\mu$ 
15   foreach  $R_j \in \text{Dependents}(R_\mu)$  do
16     compute  $a_j^{new}$ 
17     if  $j \neq \mu$  then
18        $t_j = \frac{a_j}{a_j^{new}} (t_j - t) + t$ 
19     else if  $j = \mu$  then
20       generate a random number  $r \sim \text{norm}(0, 1)$ 
21        $t_\mu = t + \frac{1}{a_\mu^{new}} \ln \frac{1}{r}$ 
22        $a_j = a_j^{new}$ 
23     replace the old time  $t_j$  in  $H$  with the new value  $t_j^{new}$  and maintain the heap  $H$ 

```

---

#### 3.4.3.1 Discussion

**3.4.3.1.1 Time complexity** The computation cost of NRM scales as the logarithm of  $M$ . For each simulation step, the extraction of the smallest time, advancing the simulation to the new time and updating the state are constant. The update cost in the for dominates the total cost. It iterates over all the dependent reaction to calculate their new times and perform the heap update, for one reaction this costs  $O(\log(M))$ . Let  $D$  be the average number of reaction that are dependent on the reaction firing, then the total cost of update is  $O(D \log(M))$ . If  $D$  is small and is bounded by a constant, then the total cost is  $O(\log(M))$ . Moreover only one random number is necessary for each simulation step, so the number of random numbers used by NRM is optimal.

**3.4.3.1.2 Inactive reaction** When a reaction is inactive  $a_j = 0$  before firing  $R_\mu$  and becomes active after the reaction, the new time of  $R_j$  will be  $t_j^{new} = t_\mu$ , which is not possible. A solution for the implementation of this step is to generate a new putative time  $\tau_j^{new}$  by sampling  $e^{a_j^{new}}$  rather than applying the transformation.

### 3.4.4 Modified next reaction method

The modified next reaction method MNRM is a variant of NRM where the firing time of reaction are represented as independent Poisson processes with rates given by their integrated propensities.

#### 3.4.4.1 Poisson process

Let  $Y(t), t \geq 0$  be a process that counts the number of events by time  $t$ .  $Y(t)$  is a Poisson process with rate  $\lambda > 0$  if:

- $Y(0) = 0$ .
- $Y(t)$  has the stationary increment property:  
 $\forall [t, t + \Delta t], Y(t) - Y(t + \Delta t)$  has the same distribution as  $Y(\Delta t)$ .
- $Y(t)$  has the independent increment prop-

erty:  $\forall [t, t + \Delta t] \wedge [t', t' + \Delta t']$  such that  $[t, t + \Delta t] \cap [t', t' + \Delta t'] = \emptyset$ ,  $Y(\Delta t)$  is independent of  $Y(\Delta t')$ .

- The probability of observing one event in the infinitesimal  $[t, t + dt]$  is  $\mathbb{P}\{Y(t + dt) - Y(t) = 1\} = \lambda dt + o(dt)$

Now let  $Y(t)$  be a Poisson process with rate  $\lambda$ , then:

- The distribution  $Y(t), t \geq 0$  is a Poisson distribution  $poi(\lambda t)$ .
- The time to the next event of the Poisson process is an exponential distribution  $exp(\lambda)$ .

**3.4.4.1.1  $Y(t)$  is a Poisson distribution** To prove the first claim let  $\mathbb{P}\{Y(t) = k\}$  be the probability that there are  $k$  events in  $[0, t]$ . Suppose that this is divided into intervals  $[\frac{(i-1)t}{n}, \frac{it}{n}]$  of length  $\frac{t}{n}$  such that there is at most one event in each subinterval. The number of events in  $[0, t]$  is the sum of the events observed in the subintervals. By definition of  $Y(t)$ , the probability of observing an event in the subinterval is  $\frac{\lambda t}{n}$ . The probability  $\mathbb{P}\{Y(t) = k\}$  follows a binomial distribution with success probability  $\frac{\lambda t}{n}$ :

$$\mathbb{P}\{Y(t) = k\} = \binom{n}{k} \left(\frac{\lambda t}{n}\right)^k \left(1 - \frac{\lambda t}{n}\right)^{n-k} = \frac{n!}{k!(n-k)!} \left(\frac{\lambda t}{n}\right)^k \left(1 - \frac{\lambda t}{n}\right)^{n-k}$$

Expanding the factorial and taking the limit  $n \rightarrow \infty$ :

$$\begin{aligned} \mathbb{P}\{Y(t) = k\} &= \lim_{n \rightarrow \infty} \frac{n}{n} \frac{n-1}{n} \dots \frac{n-k-1}{n} \left(1 - \frac{\lambda t}{n}\right)^{-k} \frac{(\lambda t)^k}{k!} \left(1 - \frac{\lambda t}{n}\right)^n = \\ &= \frac{(\lambda t)^k e^{-\lambda t}}{k!} \end{aligned}$$

Considering that  $\lim_{n \rightarrow \infty} \left(1 - \frac{\lambda t}{n}\right)^n = e^{-\lambda t}$ . In conclusion then the probability  $\mathbb{P}\{Y(t) = k\}$  denotes a Poisson distribution  $poi(\lambda t)$ .

**3.4.4.1.2 The time to the next event is an exponential distribution** Let  $T$  be the time to the next event of the Poisson process  $Y(t)$ . By definition of the Poisson process, it only needs to consider the time to the first event after 0. Let  $F_T$  be the cdf of  $T$ :

### 3.4. NEXT REACTION METHOD

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$$F_T(t) = \mathbb{P}\{T \leq t\} = \mathbb{P}\{Y(t) \geq 1\} = 1 - \mathbb{P}\{Y(t) = 0\} = 1 - \frac{(\lambda t)^0 e^{-\lambda t}}{0!} = 1 - e^{-\lambda t}$$

Considering that  $\mathbb{P}\{Y(t) \geq 1\} = \mathbb{P}\{T \leq t\}$ . This shows that the time  $T$  to the next event follows an exponential distribution  $\exp(\lambda)$ .

#### 3.4.4.2 Unit Poisson process

The Poisson process with rate 1 is called a unit Poisson process. If  $Y(t)$  denotes a unit Poisson process, then  $T(\lambda t)$  is a Poisson process with rate  $\lambda$ .

#### 3.4.4.3 Random time change representation

Let  $C_j(t)$  be the number of times that  $R_j$  fires up to  $t$ .  $C(t)$  satisfies the conditions of the Poisson process. The probability that  $R_k$  fires in  $[t, t + dt]$  by definition of  $a_j$  is:

$$\mathbb{P}\{C_j(t + dt) - C_j(t) = 1 | X(s), s \leq t\} = a_j(X(t))dt + o(dt)$$

$C_j(t)$  denotes a Poisson process with rate  $a_j(X(T))$ . Let  $Y_j(t)$  be an independent unit Poisson process.  $C_j(t)$  is represented in MNRN in term of  $Y_j(t)$ . It can be noted how:

$$C_j(t) = Y_j \left( \int_0^t a_j(X(s))ds \right)$$

Or the random time change RTC representation.

#### 3.4.4.4 Internal time

The internal time  $I_j$  of  $Y_j$  associated with  $R_j$  is:

$$I_j(t) = \int_0^t a_j(X(s))ds$$

$I_j(t)$  given  $t$  shows the amount of time that  $Y_j$  passed before it expires due to the firing of  $R_j$ . Each reaction can be seen as carrying its own internal clock, with a rate given by the integration of the propensity. There are  $M + 1$  time frames in which the first is the physical time  $t$  and the last  $M$  are for  $M$  Poisson processes  $Y_j$ . The internal time is a dimensionless quantity.

**3.4.4.4.1 Computing the tentative time** Let  $t$  be the current time, the system state is  $X(t) = \vec{x}$ . The propensity  $a_j$  and the internal time is  $T_j = I_j(t)$ . The internal time at time  $t = 0$  is  $I_j(0) = 0$ . Let  $P_j$  be the next internal event time of  $Y_j$  with corresponding physical time  $t_j > t$ ,  $P_j = I_j(t)$ . The relationship between  $T_j$  and  $P_j$  is:

$$P_j = I_j(t_j) = I_j(t) + a_j(t_j - t) = T_j + a_j\tau_j$$

Where  $\tau_j = t_j - t$  is the relative time to the firing of  $R_j$ . The amount of internal time to the firing is  $a_j\tau_j$ . Because  $Y_j$  is a unit Poisson process, the time to the next firing follows a distribution  $\exp(1)$ : the amount  $P_j - T_j$  is an exponentially distributed random number with rate 1. If the current internal time  $T_j$  and the next internal time  $P_j$  are tracked, the tentative time to the firing, given that no other reaction fires before is:

$$\tau_i = \frac{P_j - T_j}{a_j}$$

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The selection with minimum  $\tau_\mu$  will be selected to fire.

**3.4.4.4.2 Updating the firing time** Suppose that the reaction  $R_\mu$  fires at time  $t_\mu = t + \tau_\mu$ . The next internal event time  $P_j$  of  $Y_\mu$  must be generated because it expired, the new time is computed as:

$$\tau_i = \frac{P_j - T_j}{a_j}$$

For reaction  $R_j$ , with  $j \neq \mu$ , the updated internal time of process  $Y_j$  at time  $t + \tau_\mu$  is:

$$I_j(t + \tau_\mu) = I_j(t) + a_j \tau_\mu$$

Let  $a_j^{new}$  be the new propensity and  $\tau_j^{new}$  be the new tentative time to firing  $R_j$  after the firing of  $R_\mu$ .  $a_j^{new} \tau_j^{new}$  is the remaining amount of internal time to the next firing of  $Y_j$ . Because the processes are independent, the next internal event time  $P_j$  of  $Y_j$  does not change:

$$P_j = I_j(t + \tau_\mu) + a_j^{new} \tau_j^{new} = I_j(t) + a_j \tau_\mu + a_j^{new} \tau_j^{new}$$

Comparing it with the other computation of  $P_j$ :

$$\tau_j^{new} = \frac{a_j}{a_j^{new}} (\tau_j - \tau_\mu) = \frac{a_j}{a_j^{new}} (t_j - t_\mu)$$

Then the absolute time to the next firing of  $R_j$ :

$$t_j^{new} = t_\mu + \tau_j^{new} = \frac{a_j}{a_j^{new}} (\tau_j - \tau_\mu) + t_\mu$$

Which is the transformation used by NRM: the selection of the next reaction firing is exact.

#### 3.4.4.5 Algorithm

An implementation of MNRM is outlined in algorithm 18.

### 3.5. REJECTION BASED STOCHASTIC SIMULATION ALGORITHM

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**Algorithm 18:** Modified Next Reaction Method (MNRM)()

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```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$   

2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$   

3  $t = 0$   

4  $\vec{X} = \vec{x}_0$   

5 build the reaction dependency graph  $G$   

6 foreach  $R_j$  do  

7    $T_j = 0$   

8   generate a random number  $r_j \sim \text{norm}(0, 1)$   

9    $P_j = \ln \frac{1}{r_j}$   

10  compute  $a_j$   

11 while  $t < T_{\max}$  do  

12   foreach  $R_j$  do  

13      $\tau_j = \frac{1}{a_j}(P_j - T_j)$   

14   select  $R_\mu$  with the smallest time  $\tau = \min_{j=1}^M \{\tau_j\}$   

15    $\vec{X} = \vec{X} + \vec{v}_\mu$   

16    $t = t + \tau$   

17   foreach  $R_j$  do  

18      $T_j = T_j + a_j \tau$   

19     if  $j = \mu$  then  

20       generate a random number  $r \sim \text{norm}(0, 1)$   

21        $P_\mu = P_\mu + \ln \frac{1}{r}$   

22     if  $R_j \in \text{Dependents}(R_\mu)$  then  

23       compute new  $a_j$ 

```

---

**3.4.4.5.1 Discussion** The simulation of MNRM is equivalent to NRM. MNRM explicitly works with internal time arising from the RTC representation, while NRM works with physical time. This makes MNRM more flexible to handle complex propensity function and helps make a smooth connection between exact stochastic simulation and the class of Poisson approximation, like the  $\tau$ -leaping algorithm.

## 3.5 Rejection Based stochastic simulation algorithm

The rejection based stochastic simulation algorithm or RSSA is an exact simulation algorithm that tries to reduce the number of propensity updates during the simulation. Each simulation iteration selects a  $R_\mu$  with probability  $\frac{a_\mu}{a_0}$  and its firing time is exponentially distributed according to  $a_0$ . The selection of the next reaction firing in RSSA is an acceptance-rejection sampling technique that allows to skip the propensity updates in most of the iterations. They are recomputed only when necessary. Because of this it is useful for reaction in which propensities are complex.

### 3.5.1 Fluctuation interval

For each species  $S_i$  RSSA abstracts its exact population  $X_i(t)$  with a fluctuation interval  $[\underline{X}_i, \bar{X}_i]$ . The interval can be chosen arbitrarily around the current population without affecting the correctness of the algorithm. The fluctuation interval can be defined as:

$$[\underline{X}_i, \bar{X}_i] = [(1 - \delta_i)X_i(t), (1 + \delta_i)X_i(t)]$$

Where  $\delta_i$  is the parameter called fluctuation rate. A good choice for real biological model is from 10 to 20% of current population of species. Considering abstraction interpretation terminology,  $X(t)$  is called the concrete state, while  $[\underline{X}, \bar{X}]$  is the abstract state. For each species holds:

$$\underline{X} \leq X(t) \leq \bar{X}$$

### 3.5.2 Abstract propensity value

For each  $R_j$  an abstract propensity value  $[\underline{a}_j, \bar{a}_j]$  is computed, this is an interval encompassing all its possible values, including the exact one  $a_j(X(t))$ . The bounds are derived by minimizing and maximizing  $a_j$  over the fluctuation interval. For the standard mass action or Michaelis-Menten kinetics,  $a_j$  is a monotonic function of the state  $X$ , so that  $\underline{a}_j = a_j(\underline{X})$  and  $\bar{a}_j = a_j(\bar{X})$ . If it is non-monotonic, a numerical optimization technique or interval analysis can be applied to recover the bounds. The exact bounds are not needed as the tight bounds of  $a_j$  over the fluctuation interval are sufficient.

### 3.5.3 Selection of the next reaction

The selection of the next reaction has two steps:

- Simulation of the abstract model.
- Acceptance of the candidate reaction.

#### 3.5.3.1 Simulation of the abstract model

In the first step RSSA simulates the abstract model assigning to each  $R_j \frac{\bar{a}_j}{\bar{a}_0}$ , where  $\bar{a}_0 = \sum_{j=1}^M \bar{a}_j$ .  $R_\mu$  is randomly selected with probability  $\frac{\bar{a}_\mu}{\bar{a}_0}$  as a candidate. The realization of  $R_\mu$  is performed accumulating propensity upper bounds until the smallest  $\mu$  is selected such that:

$$\sum_{j=1}^{\mu} \bar{a}_j \geq r_1 \bar{a}_0$$

Where  $r_1 \sim \text{norm}(0, 1)$ .

#### 3.5.3.2 Acceptance of the abstract model

In the second step RSSA checks whether  $R_\mu$  is accepted to occur in the concrete model through a rejection test with success probability  $\frac{a_\mu}{\bar{a}_\mu}$ . Since the exact value of the propensity is not known, a random number  $r_2 \sim \text{norm}(0, 1)$  is drawn to check whether:

$$r_2 \leq \frac{a_\mu}{\bar{a}_\mu}$$

### 3.5. REJECTION BASED STOCHASTIC SIMULATION ALGORITHM

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If this succeeds  $R_\mu$  is accepted because  $r_2 \leq \frac{a_\mu}{\bar{a}_\mu} \leq \frac{a_\mu}{\hat{a}_\mu}$ . When this fails  $a_\mu$  is computed and  $r_2$  is tested against  $\frac{a_\mu}{\hat{a}_\mu}$ . This happens infrequently when  $\frac{a_\mu}{\hat{a}_\mu}$  is close to 1. If  $R_\mu$  is accepted the firing time is computed, otherwise a new reaction is selected and tested again.

#### 3.5.4 Advancement of the simulation

To remain exact RSSA has to advance the simulation at every attempt of rejection by an exponentially distributed variable with parameter  $\bar{a}_0$ . Assuming  $k-1$  reactions and following the acceptance, the simulation has to advance by a quantity equal to the sum of  $k$  exponential random numbers:

$$\frac{1}{\bar{a}_0} \ln \frac{1}{u_1} + \frac{1}{\bar{a}_0} \ln \frac{1}{u_2} + \cdots + \frac{1}{\bar{a}_0} \ln \frac{1}{u_k}$$

Where  $u_i \sim \text{norm}(0, 1)$  are independent and identically distributed random numbers. This sum is the Erlang distribution  $\text{erlang}(k, \bar{a}_0)$ .

#### 3.5.5 Exactness of RSSA

For each simulation iteration of RSSA,  $R_\mu$  is selected to fire with probability  $\frac{a_\mu}{a_0}$  and its firing time  $\tau$  follows an exponential distribution with rate  $a_0$ . Let  $\mathbb{P}\{R_\mu\}$  be the probability that  $R_\mu$  is selected and accepted to fire in a single attempt. This can be expressed as the product of the probability of being selected and being accepted:

$$\mathbb{P}\{R_\mu\} = \frac{\bar{a}_\mu}{\bar{a}_0} \frac{a_\mu}{\bar{a}_0} = \frac{a_\mu}{\bar{a}_0}$$

Let  $\mathbb{P}\{R\}$  be the probability that some reaction is accepted in a single attempt, this is:

$$\mathbb{P}\{R\} = \frac{\sum_{j=1}^M a_j}{\bar{a}_0} = \frac{a_0}{\bar{a}_0}$$

$R_\mu$  being accepted after any number of rejections is a conditional probability of accepting  $R_\mu$  knowing some reaction is accepted:

$$\mathbb{P}\{R_\mu|R\} = \frac{\frac{a_\mu}{\bar{a}_0}}{\frac{a_0}{\bar{a}_0}} = \frac{a_\mu}{a_0}$$

Demonstrating that the reaction is selected with the correct probability. Now let  $F_V$  be the cdf and  $f_V$  the pdf of  $V$ . Let  $k$  be the random variable for the number of attempts performed before accepting  $R_\mu$ .  $k$  is geometrically distributed with success probability  $\mathbb{P}\{R\}$ . Let  $\tau$  be a random variable corresponding to the simulation time advancement due to the firing of  $R_\mu$ . Let  $\mathbb{P}(\tau \leq x)$  be the probability that  $\tau \leq x$  given a reaction is accepted after some trials, the pdf of  $\tau$ :

$$\begin{aligned}
 f_\tau(x) &= \frac{\partial}{\partial x} \mathbb{P}\{\tau \leq x\} = \\
 &= \frac{\partial}{\partial x} \sum_{k_0=1}^{\infty} \mathbb{P}\{\tau \leq x | k = k_0\} \mathbb{P}\{k = k_0\} = \\
 &= \frac{\partial}{\partial x} \sum_{k_0=1}^{\infty} F_{erlang(k_0, \bar{a}_0)}(x) \frac{a_0}{\bar{a}_0} \left(1 - \frac{a_0}{\bar{a}_0}\right)^{k_0-1} = \\
 &= \sum_{k_0=1}^{\infty} \frac{\partial}{\partial x} F_{erlang(k_0, \bar{a}_0)}(x) \frac{a_0}{\bar{a}_0} \left(1 - \frac{a_0}{\bar{a}_0}\right)^{k_0-1} = \\
 &= \sum_{k_0=1}^{\infty} f_{erlang(k_0, \bar{a}_0)}(x) \frac{a_0}{\bar{a}_0} \left(1 - \frac{a_0}{\bar{a}_0}\right)^{k_0-1} = \\
 &= \sum_{k_0=1}^{\infty} \frac{\bar{a}_0^{k_0} x^{k_0-1} e^{-\bar{a}_0 x}}{(k_0-1)!} \frac{a_0}{\bar{a}_0} \left(\frac{\bar{a}_0 - a_0}{\bar{a}_0}\right)^{k_0-1} = \\
 &= a_0 e^{-\bar{a}_0 x} \sum_{k_0=1}^{\infty} \frac{(\bar{a}_0 - a_0)^{k_0-1} x^{k_0-1}}{(k_0-1)!} = \\
 &= a_0 e^{-\bar{a}_0 x} e^{x(\bar{a}_0 - a_0)} = a_0 e^{-a_0 x}
 \end{aligned}$$

Noting that:

- Partitioning  $\mathbb{P}(\tau < x)$  according to  $k$  is done because for a fixed  $k$ ,  $\tau$  is an Erlang distribution with parameters  $k$  and  $\bar{a}_0$ .
- Applying the closed form of the pdf of Erlang.
- $e^x = \sum_{n=0}^{\infty} \frac{x^n}{n!}$ .

This shows how the firing time  $\tau$  follows an exponential distribution  $\exp(a_0)$ .

### 3.5.5.1 Bounds on the acceptance probability

The acceptance probability of a single attempt  $\mathbb{P}\{R\}$  is bounded by:

$$\frac{a_0}{\bar{a}_0} \leq \mathbb{P}\{R\} = \frac{a_0}{\bar{a}_0} \leq 1$$

Tighter lower or upper bounds yield a better acceptance probability: if  $[\underline{X}, \bar{X}]$  is reduced to the concrete state  $X(t)$ , the acceptance probability is 1:

$$\underline{a_j} = \bar{a_j} = a_j$$

And RSSA is reduced to DM.

### 3.5.6 Evolution of the state

After firing  $X(t)$  is updated and RSSA checks whether the new concrete state is compatible with the abstract state:  $\underline{X_i} \leq X_i(t) \leq \bar{X_i}$  holds for each species. This is often the case as a reaction only

affects a few molecules. When this is true RSSA does not recompute the abstract propensities: the inequality  $\underline{a}_j \leq a_j \leq \bar{a}_j$  still holds for all reaction and the next reaction step can be performed. If  $X(t)$  falls outside the abstract state the abstract propensities have to be updated by redefining a new abstract state around the new concrete one and deriving the corresponding propensities. This operation can be made cheaper by observing that only the reaction affected by the species for which a new fluctuation interval has been redefined require an update of the propensity bounds. This are determined by a species-reaction RS dependency graph.

### 3.5.6.1 Species-Reaction dependency graph

Let  $\mathcal{S}$  and  $\mathcal{R}$  be the set of species and reactions in the biochemical network. The species-reaction SR dependency graph is the direct bipartite graph  $\mathcal{G}(V, E)$  having:

$$\begin{aligned} V &= \mathcal{S} \cup \mathcal{R} \\ E &= \{(s, r) \in \mathcal{S} \times \mathcal{R} | s \in \text{Reactants}(r)\} \cup \{(r, s) \in \mathcal{R} \times \mathcal{S} | s \in \text{Products}(r)\} \end{aligned}$$

This is a bipartite graph that shows the dependency of reactions on species. This allows RSSA to decide which reaction should recompute their propensity bounds. For a species  $S_i$  if its population moves out of the fluctuation interval RSSA recomputes propensity bounds of a reaction  $R_j$  if there is a directed edge from  $S_i$  to  $R_j$  in  $SR$ . The number of reaction that needs to recompute propensity bounds is equal to the out-degree of  $S_i$ . The reactions that have to recompute the propensity bounds if  $X_i(t) \notin [\underline{X}_i, \bar{X}_i]$  are defined in term of the SR as:

$$\text{ReactionAffectedBy}(S_i) = \{R_j | \exists (S_i, R_j) \in \mathcal{G}\}$$

### 3.5.7 Algorithm

An implementation of RSSA is outlined in algorithm 19.

### 3.5. REJECTION BASED STOCHASTIC SIMULATION ALGORITHM

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**Algorithm 19:** Rejection-Based SSA (RSSA)()

---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$ 
2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$ 
3  $t = 0$ 
4  $\vec{X} = \vec{x}_0$ 
5 build the species reaction SR dependency graph  $\mathcal{G}$ 
6 foreach  $S_i \in Species$  do
7   define a new  $[X_i, \bar{X}_i]$  around  $X_i$ 
8  $\bar{a}_0 = 0$ 
9 foreach  $R_j \in Reactions$  do
10  compute  $\bar{a}_j$  and  $\underline{a}_j$ 
11   $\bar{a}_0 = \bar{a}_0 + \bar{a}_j$ 
12 while  $t < T_{\max}$  do
13   repeat
14      $u = 1$ 
15     accepted = false
16     repeat
17       generate three random numbers  $r_1, r_2, r_3 \sim norm(0, 1)$ 
18       select  $R_\mu$  with minimum  $\mu$  such that  $\sum_{j=1}^{\mu} \bar{a}_j \geq r_1 \bar{a}_0$ 
19       if  $r_2 \leq \frac{\underline{a}_\mu}{\bar{a}_\mu}$  then
20         accepted = true
21       else
22         evaluate  $a_\mu$  with state  $X$ 
23         if  $r_2 \leq \frac{\underline{a}_\mu}{a_\mu}$  then
24           accepted = true
25        $u = u \cdot r_3$ 
26     until accepted
27      $\tau = \frac{1}{\bar{a}_0} \ln(u)$ 
28      $\vec{X} = \vec{X} + \vec{v}_\mu$ 
29      $t = t + \tau$ 
30   until  $\exists(X_i \notin [X_i, \bar{X}_i])$ 
31   foreach  $X \notin [X_i, \bar{X}_i]$  do
32     define a new  $[X_i, \bar{X}_i]$  around  $X_i$ 
33     foreach  $R_j \in ReactionsAffectedBy(S_i)$  do
34       compute new propensity bounds  $\bar{a}_j$  and  $\underline{a}_i$ 
35       update  $\bar{a}_0$ 

```

---

### 3.5.7.1 Discussion

**3.5.7.1.1 Time complexity** The time complexity is composed of the cost to realize a candidate reaction and the number of rejection tests. RSSA accumulates propensity upper bounds linearly until it finds a candidate reaction: selecting the candidate is  $O(M)$ . Let  $\alpha = \frac{\bar{a}_0}{\bar{a}_i}$  be the average number of times the search is performed until a candidate is accepted: the cost for the selection of firing is  $O(\alpha M)$ . This cost is compensated by a huge reaction in propensity updates: let  $T_{DM}^{update}$  be the cost for propensity updates in DM. In RSSA is  $\frac{T_{DM}^{update}}{\beta}$ , where  $\beta$  is the average number of skipped updates and is the average frequency of  $X(t) \in [\underline{X}, \bar{X}]$ , providing a significant improvement for the simulation performance.

## 3.5.8 Simultaneous RSSA

Simultaneous RSSA SRSSA is a variant of RSSA that generates multiple independent trajectories in a simulation run. The propensity bounds in SRSSA are computed once and shared across the simulations, reducing the memory requirements to store the propensity bounds. The recomputing is performed collectively in a single operation which reduces the total number of propensity updates and improves the simulation performance.

### 3.5.8.1 Global fluctuation interval

Let  $K$  be the number of trajectories and  $X^r$  the system state of the  $r$ -th realization with  $r = 1, \dots, K$ . Let  $a_j^r$  the propensity of reaction  $R_j$  in the  $r$ -th realization. A lower and upper bound for each  $R_j$  such that  $\underline{a}_j \leq a_j^r \leq \bar{a}_j \forall r = 1, \dots, K$  and uses these for all  $K$  realization. It stores only  $M$  propensity bounds, which are derived by first defining a global fluctuation interval  $[\underline{X}, \bar{X}]$  which bounds all possible population in all  $K$  states  $X^r$ . Then  $a_j$  is minimized or maximized  $a_j$  on the global interval, which can be defined as  $X_i^{\min} = \min(X_i^1, \dots, X_i^K)$  and  $X_i^{\max} = \max(X_i^1, \dots, X_i^K)$  respectively to be the minimum and maximum of species  $S_i$  in all  $K$  states. Then the population interval:

$$[\underline{X}_i, \bar{X}_i] = [(1 - \delta_i)X_i^{\min}, (1 + \delta_i)X_i^{\max}]$$

Will bound al population  $S_i$  in  $K$  states, where  $\delta_i$  is the fluctuation rate of the species. The new global population intervals are redefined only when all  $K$  trajectories are stopped.

### 3.5.8.2 Algorithm

An implementation of SRSSA is outlined in algorithm 20.

#### Algorithm 20: Simultaneous RSSA (SRSSA) ()

- 1 **Input:** a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$  and the number of generated trajectories  $K$
- 2 **Output:**  $K$  independent trajectory of the biochemical reaction network, which is a collection of states  $X^r(t)$  for time  $0 \leq t \leq T_{\max}$

### 3.5. REJECTION BASED STOCHASTIC SIMULATION ALGORITHM

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```

1 foreach  $Trajectory \in K$  do
2    $t^r = 0$ 
3    $\vec{X}^r = \vec{x}_0$ 
4   build the species reaction SR dependency graph  $\mathcal{G}$ 
5   foreach  $S_i \in Species$  do
6     define a new  $[\underline{X}_i, \overline{X}_i]$  around  $X_i$ , such that  $\underline{X}_i \leq X_i^1, \dots, X_i^K \leq \overline{X}_i$ 
7    $\overline{a}_0 = 0$ 
8   foreach  $R_j \in Reactions$  do
9     compute  $\overline{a}_j$  and  $\underline{a}_j$ 
10     $\overline{a}_0 = \overline{a}_0 + \overline{a}_j$ 
11  repeat
12     $UpdateSpeciesSet = \emptyset$ 
13    foreach  $r = 1 \rightarrow K$  do
14      repeat
15         $u = 1$ 
16        accepted = false
17        repeat
18          generate three random numbers  $r_1, r_2, r_3 \sim norm(0, 1)$ 
19          select  $R_\mu$  with minimum  $\mu$  such that  $\sum_{j=1}^\mu \overline{a}_j \geq r_1 \overline{a}_0$ 
20          if  $r_2 \leq \frac{a_\mu}{\overline{a}_\mu}$  then
21            accepted = true
22          else
23            evaluate  $a_\mu^r$  with state  $X^r$ 
24            if  $r_2 \leq \frac{a_\mu}{\overline{a}_\mu}$  then
25              accepted = true
26             $u = u \cdot r_3$ 
27            until accepted
28             $\tau^r = \frac{1}{a_0} \ln(u)$ 
29             $\vec{X}^r = \vec{X}^r + \vec{v}_\mu$ 
30             $t^r = t^r + \tau^r$ 
31        until  $\exists(X_i^r \notin [\underline{X}_i, \overline{X}_i]) \vee t^r \geq T_{max}$ 
32        foreach  $S_i$  where  $X_i^r \notin [\underline{X}_i, \overline{X}_i]$  do
33           $UpdateSpeciesSet = UpdateSpeciesSet \cup \{S_i\}$ 
34      foreach  $S_i \in UpdateSpeciesSet$  do
35        define a new  $[\underline{X}_i, \overline{X}_i]$  such that  $\underline{X}_i \leq X_i^1, \dots, X_i^K \leq \overline{X}_i$ 
36        foreach  $R_j \in ReactionsAffectedBy(S_i)$  do
37          compute new propensity bounds  $\overline{a}_j$  and  $\underline{a}_i$ 
38          update  $\overline{a}_0$ 
39  until  $t^r \geq T_{max} \forall r = 1, \dots, K$ 

```

---

### 3.5.9 Improvements for RSSA

The search for a candidate reaction in RSSA is linear and becomes a computational bottleneck for large reaction networks.

#### 3.5.9.1 RSSA with tree-based search

The tree-based search can be used to reduce the time complexity of the search for the next reaction to logarithmic time. The tree stores the propensity upper bounds in the RSSA case: the search time for the candidate reaction is  $O(\log M)$  and a tree updated is performed in  $O(\log M)$ . The time complexity of the algorithm is  $O(\log M)$ .

**3.5.9.1.1 Algorithm** An implementation of RSSA with tree-based search can be found in algorithm 21.

### 3.5. REJECTION BASED STOCHASTIC SIMULATION ALGORITHM

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---

**Algorithm 21:** Rejection-Based SSA with Tree-based search()

---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$   

2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$   

3  $t = 0$   

4  $\vec{X} = \vec{x}_0$   

5 build the species reaction SR dependency graph  $\mathcal{G}$   

6 foreach  $S_i \in Species$  do  

7   define a new  $[X_i, \bar{X}_i]$  around  $X_i$   

8  $\bar{a}_0 = 0$   

9 foreach  $R_j \in Reactions$  do  

10  compute  $\bar{a}_j$  and  $\underline{a}_j$   

11   $\bar{a}_0 = \bar{a}_0 + \bar{a}_j$   

12 build TREE structure for  $M$  propensity upper bounds  $\bar{a}_j$  by build_tree  

13 while  $t < T_{\max}$  do  

14   repeat  

15      $u = 1$   

16     accepted = false  

17     repeat  

18       generate three random numbers  $r_1, r_2, r_3 \sim norm(0, 1)$   

19       select  $R_\mu$  by search_tree  

20       if  $r_2 \leq \frac{\underline{a}_\mu}{\bar{a}_\mu}$  then  

21         accepted = true  

22       else  

23         evaluate  $a_\mu$  with state  $X$   

24         if  $r_2 \leq \frac{\underline{a}_\mu}{\bar{a}_\mu}$  then  

25           accepted = true  

26        $u = u \cdot r_3$   

27     until accepted  

28      $\tau = \frac{1}{\bar{a}_0} \ln(u)$   

29      $\vec{X} = \vec{X} + \vec{v}_\mu$   

30      $t = t + \tau$   

31   until  $\exists (X_i \notin [X_i, \bar{X}_i])$   

32   foreach  $X \notin [X_i, \bar{X}_i]$  do  

33     define a new  $[X_i, \bar{X}_i]$  around  $X_i$   

34     foreach  $R_j \in ReactionsAffectedBy(S_i)$  do  

35       compute new propensity bounds  $\bar{a}_j$  and  $\underline{a}_i$   

36       update the Tree bu algorithm update_tree  

37       update  $\bar{a}_0$ 

```

---

### 3.5.9.2 RSSA with composition-rejection search

RSSA with composition-rejection search RSSA-CR employs composition-rejection search. The reaction are partitioned into  $L$  groups using the propensity bounds.  $R_j$  is put into  $G_l$  if  $2^{u_l-1} \leq \bar{a}_j < 2^{u_l}$  where  $u_l = \lceil \log_2(\bar{a}_j) \rceil$ . Let  $p_l = \sum_{R_j \in G_l} \bar{a}_j$  and  $p_o = \sum_{l=1}^L p_l = \sum_{j=1}^M \bar{a}_j = \bar{a}_0$ .

**3.5.9.2.1 Selection of the next reaction** The selection of the next reaction is a two step process:

- Selection of the group.
- Selection of a reaction.

**3.5.9.2.1.1 Selection of a group** A group  $G_\alpha$  is selected with probability  $\frac{p_\alpha}{p_0}$  by linearly accumulating  $p_l$  until a minimum  $\alpha$  such that  $\sum_{l=1}^{\alpha} p_l \geq r_1 p_0$  is found, where  $r_0 \sim \text{norm}(0, 1)$ .

**3.5.9.2.1.2 Selection of a reaction** The selection of  $R_\mu$  has two consecutive acceptance-rejection tests: the first randomly selects  $R_\mu \in G_\alpha$  and accepts it with probability  $\frac{\bar{a}_\mu}{2^{\mu\alpha}}$ . This is repeated until  $R_\mu$  is accepted. Then a second test with acceptance probability  $\frac{a_\mu}{\bar{a}_\mu}$  is performed. If the test fails both  $R_\mu$  and  $G_\alpha$  are rejected.

**3.5.9.2.2 Firing time** The firing time is generated by sampling  $\text{erlang}(k, p_0)$ , but the number of trials  $k$  counts only the second rejection test.

**3.5.9.2.3 Algorithm** An implementation of RSSA with composition-rejection search can be found in algorithm 22.

---

#### Algorithm 22: Rejection-Based SSA (RSSA) ()

---

- 1 **Input:** a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$
  - 2 **Output:** a trajectory of the biochemical reaction network, which is a collection of states  $X(t)$  for time  $0 \leq t \leq T_{\max}$
-

---



---

```

1  $t = 0$ 
2  $\vec{X} = \vec{x}_0$ 
3 build the species reaction SR dependency graph  $\mathcal{G}$ 
4 foreach  $S_i \in Species$  do
5   define a new  $[X_i, \bar{X}_i]$  around  $X_i$ 
6  $\bar{a}_0 = 0$ 
7 foreach  $R_j \in Reactions$  do
8   compute  $\bar{a}_j$  and  $a_j$ 
9    $\bar{a}_0 = \bar{a}_0 + \bar{a}_j$ 

10 group  $M$  reaction into  $L$  groups so that  $R_j \in G_l$  if  $2^{u_l-1} \leq \bar{a}_j < 2^{u_l}$ 
11  $p_0 = \sum_{l=1}^K p_l$ 
12 while  $t < T_{\max}$  do
13   repeat
14      $u = 1$ 
15     accepted = false
16     repeat
17       generate three random numbers  $r_1 \sim norm(0, 1)$ 
18       select minimum group index  $\alpha$  such that  $\sum_{l=1}^{\alpha} p_l \geq r_1 p_0$ 
19       repeat
20         generate a random number  $r_2 \sim norm(0, 1)$ 
21          $\mu = [r_2 \cdot |G_{\alpha}|]$ 
22          $r_2 = r_2 |G_{\alpha}| - \mu$ 
23       until  $r_2 = r_2 |G_{\alpha}| - \mu$ 
24       generate two random numbers  $r_3, r_4 \sim norm(0, 1)$ 
25       if  $r_3 \leq \frac{a_{\mu}}{\bar{a}_{\mu}}$  then
26         accepted = true
27       else
28         evaluate  $a_{\mu}$  with state  $X$ 
29         if  $r_3 \leq \frac{a_{\mu}}{\bar{a}_{\mu}}$  then
30           accepted = true
31        $u = u \cdot r_4$ 
32     until accepted
33      $\tau = \frac{1}{p_0} \ln(u)$ 
34      $\vec{X} = \vec{X} + \vec{v}_{\mu}$ 
35      $t = t + \tau$ 
36   until  $\exists(X_i \notin [X_i, \bar{X}_i])$ 
37   foreach  $X \notin [X_i, \bar{X}_i]$  do
38     define a new  $[X_i, \bar{X}_i]$  around  $X_i$ 
39     foreach  $R_j \in ReactionsAffectedBy(S_i)$  do
40       compute new propensity bounds  $\bar{a}_j$  and  $a_i$ 
41       update  $G_l$  with its  $p_l$  and sum  $p_0$ 

```

---

### 3.5.9.2.4 Discussion

**3.5.9.2.4.1 Time complexity** The time complexity consist of the cost of selecting the group in  $O(L)$  and the average number of times that the validation test is performed to accept a reaction is  $\alpha = \frac{2\bar{a}_\mu}{a_\mu}$ , which is dependent on the ratio of the propensity bounds which can be tuned through the fluctuation interval. The total computational cost for the selection of a reaction is  $O(L)$ .

### 3.5.9.3 RSSA with table-lookup search

The alias table lookup search is a constant time search but it requires an expensive pre-processing step to build the lookup tables. Any discrete probability distribution over  $M$  probability values can be expressed as an equi-probable mixture of  $M$  two-points distribution. The  $M$  probabilities are  $\frac{\bar{a}_j}{\bar{a}_0}$ . The setup requires to build two tables implemented as arrays of size  $M$  in which the first, the cut-off table  $Q$ , stores the first values of the two point mixture and the second, the alias table  $A$ , contains the alias to the second part.

**3.5.9.3.1 Building the tables** When building the tables the objective is to transform the  $M$  probabilities into a square histogram. The probabilities greater than average are stored in the *Greater* set and the smaller in the *Smaller* one. For each loop an element of *Greater* and an element of *Smaller* are selected. The element from *Greater* transfer a part of its value to the smaller one from *Smaller* to make it average. This step implies that for  $l \in \text{Smaller}$  such that  $Q_l < 1$  there is no alias. This is repeated until all elements in *Smaller* are reprocessed. To show that it will never reach a deadlock consider the invariant of the while loop, the sum of element in *Greater* and *Smaller* is:

$$\text{Total} = \sum_{j=1}^M Q_j = M$$

The average value will be 1. For each loop  $l \in \text{Smaller}$  with value  $Q_l$  is removed and value  $Q_k$  of  $k \in \text{Greater}$  is reduced by  $1 - Q_l$ . The total sum is reduced by 1, so the loss after the  $i$ -th loop is:

$$\text{Loss} = \sum_{k=1}^i 1 = i$$

The total number of elements in the sets is  $M - i$ : in each loop one element from *Smaller* is removed. The average value of elements in the sets after the  $i$ -th loop is:

$$\frac{\text{Total} - \text{Loss}}{M - i} = 1$$

For each loop, if *Smaller* is not empty there is at least one element in *Greater*, proving the claim. This procedure is outlined in algorithm 23.

### 3.5. REJECTION BASED STOCHASTIC SIMULATION ALGORITHM

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---

**Algorithm 23:** build\_alias\_table()

---

```

1 Input:  $M$  probabilities  $\frac{\bar{a}_j}{\bar{a}_0}$ 
2 Output: alias table  $A$  with size  $M$  storing reaction indices and cut-off table  $Q$  with size  $M$ 
   storing cut-off probabilities
3 foreach  $j = 1 \rightarrow M$  do
4    $Q_j = M \frac{\bar{a}_j}{\bar{a}_0}$ 
5    $Greater = \emptyset$ 
6    $Smaller = \emptyset$ 
7   foreach  $j = 1 \rightarrow M$  do
8     if  $Q_j \geq 1$  then
9       add  $j$  to  $Greater$ 
10    else
11      add  $j$  to  $Smaller$ 
12 while  $Greater \neq \emptyset \wedge Smaller \neq \emptyset$  do
13   take  $k \in Greater$  and  $l \in Smaller$ 
14    $A_l = k$ 
15   remove  $l$  from  $Smaller$ 
16    $Q_k = Q_k - (1 - Q_l)$ 
17   if  $Q_k < 1$  then
18     move  $k$  from  $Greater$  to  $Smaller$ 

```

---

**3.5.9.3.2 Search for the candidate reaction** The search considers a random number  $r \sim norm(0, 1)$  as the parameter. First a random index  $\mu = [Mr]$  is computed, where  $[ - ]$  is the truncation operator.  $r$  is rescaled and compared against  $Q_\mu$  the probability cut-off. If  $r < Q_\mu$   $\mu$  is returned, otherwise the reaction index in  $A_\mu$  is returned. This procedure is outlined in algorithm 24.

---

**Algorithm 24:** search\_alias\_table( $r$ )

---

```

1 Input: alias array  $A$  with size  $M$  storing reaction indices and cut-off array  $Q$  with size  $M$ 
   storing cut-off probabilities, and a random number  $r \sim norm(0, 1)$ 
2 Output: a candidate reaction  $R_\mu$  with probability  $\frac{\bar{a}_\mu}{\bar{a}_0}$ 
3  $\mu = [Mr]$ 
4  $r = Mr - \mu$ 
5 if  $r < Q_\mu$  then
6   return  $\mu$ 
7 else
8   return  $A_\mu$ 

```

---

**3.5.9.3.3 Algorithm** An implementation of RSSA with table-lookup search is outlined in algorithm 25.

### 3.5. REJECTION BASED STOCHASTIC SIMULATION ALGORITHM

---



---

**Algorithm 25:** Rejection-Based SSA (RSSA)()

---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$ 
2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$ 
3  $t = 0$ 
4  $\vec{X} = \vec{x}_0$ 
5 build the species reaction SR dependency graph  $\mathcal{G}$ 
6 foreach  $S_i \in Species$  do
7   define a new  $[X_i, \bar{X}_i]$  around  $X_i$ 
8  $\bar{a}_0 = 0$ 
9 foreach  $R_j \in Reactions$  do
10  compute  $\bar{a}_j$  and  $\underline{a}_j$ 
11   $\bar{a}_0 = \bar{a}_0 + \bar{a}_j$ 
12 build alias tables for  $M$  probabilities  $\frac{\bar{a}_j}{\bar{a}_0}$  by build_alias_table()
13 while  $t < T_{\max}$  do
14   repeat
15      $u = 1$ 
16     accepted = false
17     repeat
18       generate three random numbers  $r_1, r_2, r_3 \sim norm(0, 1)$ 
19       select  $R_\mu$  by build_alias_table( $r_1$ )
20       if  $r_2 \leq \frac{a_\mu}{\bar{a}_\mu}$  then
21         accepted = true
22       else
23         evaluate  $a_\mu$  with state  $X$ 
24         if  $r_2 \leq \frac{a_\mu}{\bar{a}_\mu}$  then
25           accepted = true
26        $u = u \cdot r_3$ 
27     until accepted
28      $\tau = \frac{1}{\bar{a}_0} \ln(u)$ 
29      $\vec{X} = \vec{X} + \vec{v}_\mu$ 
30      $t = t + \tau$ 
31   until  $\exists(X_i \notin [X_i, \bar{X}_i])$ 
32   foreach  $X \notin [X_i, \bar{X}_i]$  do
33     define a new  $[X_i, \bar{X}_i]$  around  $X_i$ 
34     foreach  $R_j \in ReactionsAffectedBy(S_i)$  do
35       compute new propensity bounds  $\bar{a}_j$  and  $\underline{a}_i$ 
36       update  $\bar{a}_0$ 
37   rebuild alias tables for  $M$  probabilities  $\frac{\bar{a}_j}{\bar{a}_0}$  by build_alias_table()

```

---

**3.5.9.3.4 Discussion** The alias table lookup takes one comparison and at most two memory accesses, so  $O(1)$ . The constant time search is affected by a large computational cost for rebuilding the lookup tables, which is  $O(M)$ , but the average number of times the lookup tables rebuild is controllable through the fluctuation interval.

# Chapter 4

## Approximation algorithms

### 4.1 Introduction

Exact simulation of complex biological system is often too expensive due to their stochastic and multi scale nature. These lead to the development of approximate algorithms, which improve the simulation efficiency by sacrificing their accuracy. Multiple firings are coalesced and performed together in one simulation step with a huge speed up. Approximate methods should be used because:

- It might be the only possible and feasible solution to solve a problem.
- reality is affected by error, so even when using exact stochastic simulation algorithms a small degree of approximation should be considered. A certain deal of error could aid in retrieving a more realistic result.

In this case, each algorithm (Figure 4.1) approximates in a different way, assuming different approximations. Of the three main computational strategies presented here, there is one which is much more popular with respect to the others the  $\tau$  leaping method.

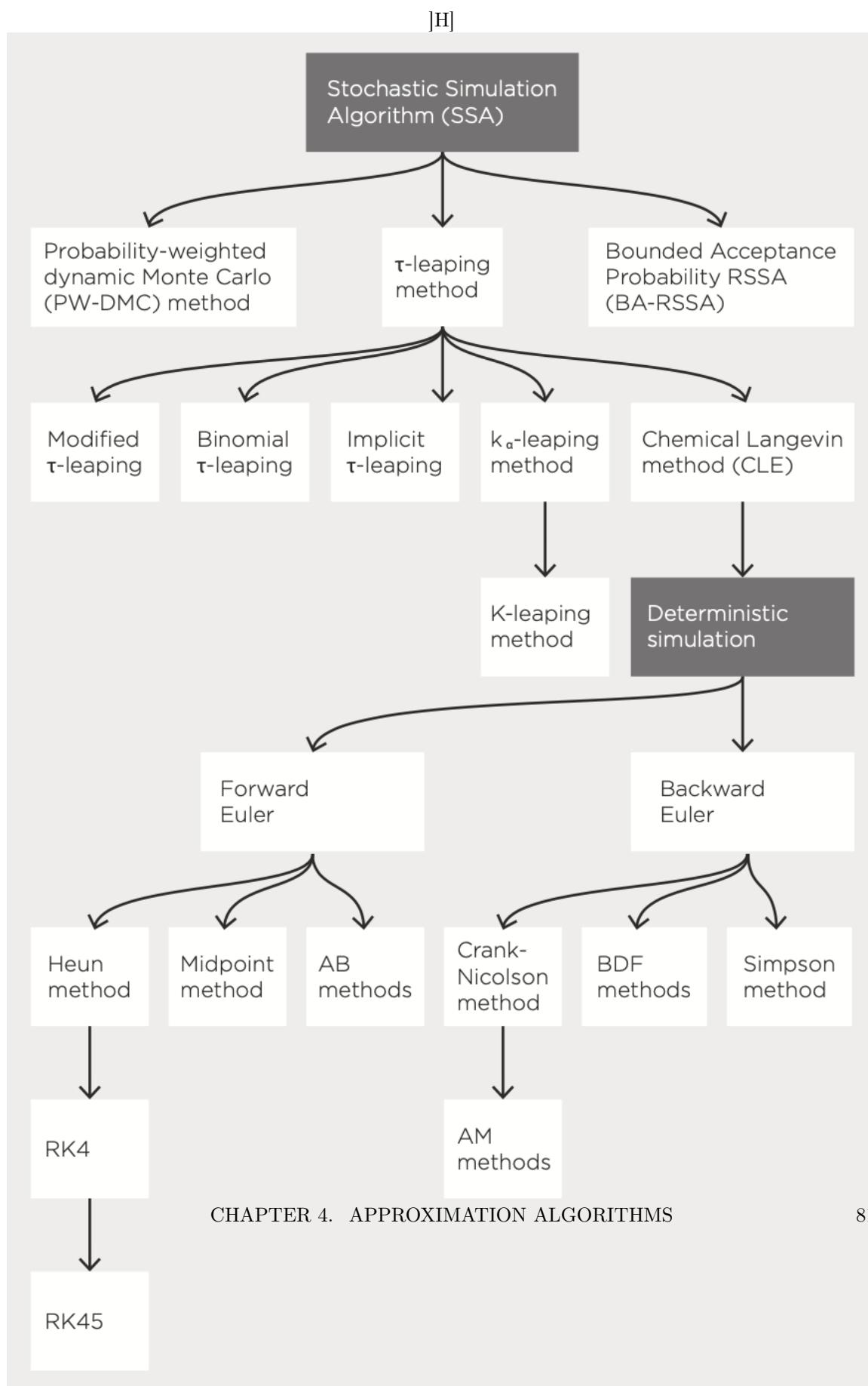
To improve the exact simulations algorithms, one should consider to:

- Work on the number of reaction events, grouping them in such a way to reduce the number of reactions in the system. The  $\tau$  leaping methodology is working in this direction.
- Improve the computation of the propensity. For instance, the probability-weighted Monte Carlo is particularly promising in situations in which there is a huge differences in propensities among reactions.

### 4.2 Probability-Weighted Dynamic Monte Carlo Method

The probability-weighted dynamic Monte Carlo method (PW-DMC) is an approximation approach for improving the computational efficiency of stochastic simulations of reaction networks where some reactions have propensities significantly larger than other reactions. This is because fast reactions (with large propensities) occur frequently and dominate the simulation, while slow reactions (with small propensities) occur less frequently. The events from the slow reaction are rare and their statistical estimation is unreliable. PW-DMC attempts to equalize the propensities of reactions so that a larger increment time step can be chosen, improving simulation's performance.

## 4.2. PROBABILITY-WEIGHTED DYNAMIC MONTE CARLO METHOD



**Figure 4.1:** Relationship between stochastic simulation algorithms

### 4.2.1 Weighted sampling

The principle of this algorithm is a sort of modification of the probability distribution of the next reaction firing through weighted sampling. The propensity  $a_j$  of  $R_j$  is scaled by a biasing weight  $w_j$  defined as the number of firing of  $R_j$  at each step. To compute it the unweighted probability  $\frac{a_j}{a_0}$  is discretized into integer valued histogram bins according to a size  $b$ .

#### 4.2.1.1 Effective propensity

The effective propensity  $a_j^w$  is computed as:

$$a_j^w = \frac{a_j}{w_j}$$

These are then used for the selection of  $R_\mu$ . The chance that a slow reaction fires is increased and so is the frequency of rate events.

### 4.2.2 Realization of the reaction firing

The realization of the next reaction firing has two step:

- Selection of the reaction.
- Correction of the firing time.

#### 4.2.2.1 Selection of the reactoin

$R_\mu$  is selected with probability  $\frac{a_\mu^w}{a_0^w}$ , where  $a_0^\mu = \sum_{j=1}^M a_j^w$ . This can be done by linearly accumulating  $a_\mu^w$  as:

$$\mu = \arg \min_{j \in \mu} \sum_{j=1}^{\mu} a_j^w \geq r_1 a_0^w$$

Where  $r_1 \sim \text{norm}(0, 1)$ .

#### 4.2.2.2 Correction of the firing time

The firing time  $\tau$  is corrected to account for the bias.  $\tau$  is generated from an exponential distribution with rate  $a_0^w$ :

$$\tau = \frac{1}{a_0^w} \ln \left( \frac{1}{r_2} \right)$$

Where  $r_2 \sim \text{norm}(0, 1)$ . Then the state at time  $t+\tau$  is updated assuming there are  $w_\mu$  consecutive firings of  $R_\mu$  in  $[t, t + \tau[$  ant the state at time  $t + \tau$  is updated as:

$$X(t + \tau) = X(t) + w_\mu \vec{v}_\mu$$

The weight of the reactions have to be updated accordingly.

### 4.2.3 Bounds on the weights

$w_j$  should be an integer value because the population of a species involved in a reaction is an integer. Its magnitude is constrained in order to bound the error in the results. Each time  $R_j$  is selected it fires  $w_j$  times. The change of each species  $S_i$  in  $R_j$  is  $w_j$ , the fluctuation of the population is thus  $\frac{w_j}{X}$ . This ratio must be less than a predefined tolerance  $\epsilon$  to ensure the statistical uncertainty of the estimation of  $X_i$ . Moreover the ration would be negligibly small when the population of species is large, and the chosen weight does not affect the simulation result. However the weight introduces an approximation to the temporal dynamics when the population of species is low and in this case  $w_j$  must be adjusted to maintain  $w_j < \epsilon X_i$ .

### 4.2.4 Algorithm

An implementation of PW-DMC can be found in algorithm 26.

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**Algorithm 26: Probability-Weighted Dynamic Monte Carlo (PW-DMC) ()**


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1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$ , the size  $b$  for discretizing  

   probability of reacitons and tolerance  $\epsilon$  for constraining the fluctuation of species.  

2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$   

3  $t = 0$   

4  $\vec{X} = \vec{x}_0$   

5 build the reaction dependency graph  $G$   

6 compute propensity  $a_j$  for each reaction  $R_j$   

7 while  $t < T_{\max}$  do  

8   compute  $w_j$  for each  $R_j$   

9   compute  $a_j^w = \frac{a_j}{w_j}$  for each  $R_j$   

10   $a_0^w = \sum_{j=1}^M a_j^w$   

11  generate two random numbers  $r_1, r_2 \sim \text{norm}(0, 1)$   

12  select  $R_\mu$  with the smallest index  $\mu$  such that  $\sum_{j=1}^\mu a_j^w \geq r_1 a_0^w$   

13   $\tau = \frac{1}{a_0^w} \ln \frac{1}{r_2}$   

14   $\vec{X} = \vec{X} + w_\mu \vec{v}_\mu$   

15   $t = t + \tau$   

16  foreach  $R_j \in \text{Dependents}(R_\mu)$  do  

17    update  $a_j$ 
```

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### 4.2.5 Discussion

#### 4.2.5.1 Time complexity

The speed-up gain in PW-DM is achieved by multiple firings of a reaction in each step. The weight can be tuned to produce a significant gain in computational performance, while keeping accuracy. The frequency of rare events is increased, helping explore more the biochemical systems.

#### 4.2.5.2 Limitations

PW-DMC skews the probability distribution of the state, because the weight sampling groups reaction of the same type in bundles and fires them together, loosing the order of reaction. PW-DMC could misdescribe the fluctuation of species in the result.  $\epsilon$  has to be set for constraining fluctuation of species to a reasonably small value in order to bound the accuracy of the simulation.

### 4.3 Bounded acceptance probability RSSA

The bounded acceptance probability RSSA BA-RSSA focuses on the simulation of reactions involved species with both small and large population. These will have a large propensity. Many firings can occur in time interval and quickly deplete the small population species. To bound the error updates must be performed frequently, degrading the simulation performance, especially if the small population is a hub species. The simulation of this reactions is accelerated by bounding the acceptance of a candidate reaction selected by RSSA. It accepts a candidate reaction without validation if its acceptance probability is greater than a user-defined probability, reducing the computational cost for both selecting of reaction firing and propensity updates.

#### 4.3.1 Defining the bounds

Let  $0 \leq \alpha \leq 1$  be a constant defined as a lower bound for the acceptance probability and  $R_j$  the selected reaction. BA-RSSA guarantees that the probability that  $R_j$  is accepted to fire is greater than  $\alpha$ . The validation step of standard RSSA accepts  $R_j$  to fire with probability  $\frac{a_j(X(t))}{\bar{a}_j}$ , the goal of BA-RSSA is to ensure:

$$\frac{a_j(X(t))}{\bar{a}_j} \geq \alpha$$

This is difficult to assess because it depends on  $X(t)$ . Anytime the state changes  $a_j$  has to be re-evaluated. To cope with this BA-RSSA exploits the fact that  $a_j(X(t)) \geq \underline{a}_j$  when  $X(t) \in [\underline{X}, \bar{X}]$ , therefore if:

$$\frac{\underline{a}_j}{\bar{a}_j} \geq \alpha$$

Holds for each reaction  $\frac{a_j(X(t))}{\bar{a}_j} \geq \alpha$  is automatically satisfied.

#### 4.3.2 Defining the fluctuation interval

To enforce  $\frac{\underline{a}_j}{\bar{a}_j} \geq \alpha$ ,  $[\underline{X}, \bar{X}]$  has to be defined so that  $\frac{\underline{a}_j}{\bar{a}_j}$  of each  $R_j$  within the fluctuation interval is bounded by  $\alpha$ . A fluctuation rate  $\delta_i$  for each  $S_i$  involved in  $R_j$  has to be selected so that when  $S_i$  fluctuates in  $[(1 - \delta_i)X_i(t), (1 + \delta_i)X_i(t)]$  the inequality is satisfied. Only a range of  $\delta_i$  can be chosen given the ratio of propensity bounds.

##### 4.3.2.1 Computing the maximum fluctuation rate

The maximum fluctuation rate  $\delta_i$  computation is reaction dependent.

**4.3.2.1.1 Synthesis reaction** For a synthesis reaction  $R_j$ ,  $a_j$  is independent of  $X(t)$  and is equal to  $x_j$ . Also the bounds are constant, the ratio is equal to 1 and the inequality is satisfied.

**4.3.2.1.2 Unimolecular reaction** For a unimolecular reaction  $R_j$ ,  $\bar{a}_j = c_j(1 + \delta_i)X_i$  and  $\underline{a}_j = c_j(1 - \delta_i)X_i$ , so that the inequality becomes:

$$\frac{1 - \delta_i}{1 + \delta_i} \geq \alpha$$

The maximum value of  $\delta_i$  then becomes:

$$\delta_i = \frac{1 - \alpha}{1 + \alpha}$$

**4.3.2.1.3 Bimolecular reaction** For a bimolecular reaction  $R_j$   $\bar{a}_j = c_j(1 + \delta_j)(1 + \delta_k)X_i X_k$  and  $\underline{a}_j = c_j(1 - \delta_i)(1 - \delta_k)X_i X_k$ , so that:

$$\frac{(1 - \delta_i)(1 - \delta_k)}{(1 + \delta_i)(1 + \delta_k)} \geq \alpha$$

Which is a quadratic equation of two independent variables, which can be splitted in to part so that:

$$\frac{1 - \delta_i}{1 + \delta_i} \geq \sqrt{\alpha} \wedge \frac{1 - \delta_k}{1 + \delta_k} \geq \sqrt{\alpha}$$

So that the maximum values for the fluctuation rates are:

$$\delta_i = \delta_k = \frac{1 - \sqrt{\alpha}}{1 + \sqrt{\alpha}}$$

**4.3.2.1.4 Dimerization reaction** For a dimerization reaction  $R_j$  by a similar derivation as the bimolecular one:

$$\frac{(1 - \delta_i)((1 - \delta_i)X_i - 1)}{(1 + \delta_i)((1 + \delta_i)X_i - 1)} \geq \alpha$$

So that the maximum  $\delta_i$ :

$$\delta_i = \frac{1 - \sqrt{\alpha}}{1 + \sqrt{\alpha}} \left( 1 - \frac{1}{X_i} \right)$$

### 4.3.3 Selecting the propensity

Once the state is confined in a fluctuation interval that satisfies the bounds, any  $b_j \in [\underline{a}_j, \bar{a}_j]$  can be chosen as the propensity. The extreme values may bias the selection step, so the average can be used:

$$b_j = \frac{\underline{a}_j + \bar{a}_j}{2}$$

### 4.3. BOUNDED ACCEPTANCE PROBABILITY RSSA

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This choice requires two evaluation of the propensity function. Another choice is to compute the value of the propensity at the central point of the fluctuation interval so to have one evaluation of the propensity function:

$$b_j = a_j \left( \frac{\underline{X} + \overline{X}}{2} \right) = a_j(X(t))$$

#### 4.3.4 Algorithm

An implementation of BA-RSSA can be found in algorithm 27.

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**Algorithm 27: Buonded Acceptance Probability RSSA (BA-RSSA) ()**

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1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$  and the bound of the  

   acceptance probability  $0 \leq \alpha \leq 1$ 
2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$ 
3  $t = 0$ 
4  $\vec{X} = \vec{x}_0$ 
5 build the species reaction SR dependency graph  $\mathcal{G}$ 
6 define  $\delta_i \forall S_i$  involved in  $R_j$  to ensure that the acceptance of  $R_j$  is bounded by  $\alpha$ 
7 compute the fluctuation interval  $[\underline{X}_i, \overline{X}_i] = [(1 - \delta - i)X_i, (1 + \delta_i)(X_i)]$  for each species  $S_i$   

   around its current population  $X_i$ 
8 compute  $b_j$  for each  $R_j$ 
9  $b_0 = \sum_{j=1}^M b_j$ 
10  $\overline{a_0} = 0$ 
11 foreach  $R_j \in Reactions$  do
12   | compute  $\overline{a_j}$  and  $\underline{a_j}$ 
13   |  $\overline{a_0} = \overline{a_0} + \overline{a_j}$ 
14 while  $t < T_{\max}$  do
15   | repeat
16     |   generate two random numbers  $r_1, r_2 \sim norm(0, 1)$ 
17     |   select minimum index  $\mu$  such that  $\sum_{j=1}^{\mu} b_j \geq r_1 b_0$ 
18     |    $\tau = \frac{1}{b_0} \ln(r_2)$ 
19     |    $\vec{X} = \vec{X} + \vec{v}_{\mu}$ 
20     |    $t = t + \tau$ 
21   | until  $\exists (X_i \notin [\underline{X}_i, \overline{X}_i])$ 
22   | foreach  $X_i \notin [\underline{X}_i, \overline{X}_i]$  do
23     |   | define a new  $[\underline{X}_i, \overline{X}_i] = [(1 - \delta - i)X_i, (1 + \delta_i)(X_i)]$ 
24     |   | foreach  $R_j \in ReactionsAffectedBy(S_i)$  do
25       |   |   | update  $b_j$  and  $b_0$ 

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### 4.3.5 Discussion

When  $\alpha = 1$  return to the exact case.

#### 4.3.5.1 Time complexity

BA-RSSA reduces the selection cost for the next reaction firing and avoids a large number of the propensity updates. The selected reaction firing is ensured to fire with probability greater than a threshold when the population is confined in its fluctuation interval. The propensity updates are performed infrequently and only locally.

## 4.4 $\tau$ -Leaping method

The aim of the  $\tau$ -leaping method is to discretize the time axis into intervals and to approximate the number of reaction firing in each one. The simulation then leaps from one interval to the next with many reaction firing performed simultaneously.

### 4.4.1 Simulation time

The simulation time is discretized into time intervals of length  $\tau$ , the leap time. This is adaptively defined during the simulation. Consider a time interval  $[t, t + \tau]$ . The joint probability  $\mathbb{P}\{k_1, \dots, k_M | \tau, \vec{x}, t\}$  gives the number of firing of reactions during the time interval given the state at time  $t$ . And is defined as the probability that there are  $k_j$  firings of  $R_j$  during the time interval. Finding an exact formula is as difficult as solving the CME, an approximation can be derived by assuming that changes in propensities due to reaction firing are insignificant, called the leap condition.

#### 4.4.1.1 Leap condition

The leap condition states that there exists a leap  $\tau > 0$  such that the change in  $a_j$  of each reaction  $R_j$  during the time interval  $[t, t + \tau]$  is negligibly small. Let now  $[t, t + \tau[$  be the time interval in which the leap condition is satisfied. The propensity of  $R_j$  during this interval given the state  $X(t) = \vec{x}$  is a constant value  $a_j(\vec{x})$ . The probability that  $R_j$  fires in  $dt \in [t, t + \tau[$  is constant and equal to  $a_j(\vec{x})dt$ , regardless if other reaction fire. Let  $\mathbb{P}\{k_j | \tau, \vec{x}, t\}$  be the probability that  $k_j$  firing of  $R_j$  happen in the interval. It can be shown that:

$$\mathbb{P}\{k_j | \tau, \vec{x}, t\} = \frac{(a_j(\vec{x})\tau)^{k_j}}{k_j!} e^{-a_j(\vec{x})\tau}$$

Which is a Poisson distribution:  $k_j$  is a Poisson distributed random number  $poi(a_j(\vec{x})\tau)$ . Because the  $M$  probabilities are statistically independent, the joint probability is:

$$\mathbb{P}\{k_1, \dots, k_M | \tau, \vec{x}, t\} = \prod_{j=1}^M \mathbb{P}\{k_j | \tau, \vec{x}, t\}$$

This allows to implement the  $\tau$ -leaping.

#### 4.4.2 Advancing the simulation time

Let  $X(t) = \vec{x}$  at time  $t$  and  $[t, t + \tau[$  that satisfies the leap condition.  $k_j$  is generated by sampling  $poi(a_j(\vec{x})\tau)$ .  $k_j$  are ensured to distribute with the joint probability. Knowing the firing times of the reaction, the method leaps down time  $t$  by  $\tau$  to the new time  $t + \tau$  and updates the state:

$$X(t + \tau) = \vec{x} + \sum_{j=1}^M k_j \vec{v}_j = \vec{x} \sum_{j=1}^M poi(a_j(\vec{x}\tau)\vec{v}_j)$$

If the number of firing during the time interval is sufficiently large the  $\tau$ -leaping method is faster than the exact simulation.

#### 4.4.3 Issues

The  $\tau$ -leaping method exposes many issues that must be addressed for a practical implementation.

##### 4.4.3.1 Efficiency and accuracy

The efficiency and accuracy are dependent on how to choose a leap  $\tau$ . If propensities are independent of the state any  $\tau$  satisfies the leap condition, making it an exact method. If the propensities are state dependent, the selection of the leap is a trade-off between simulation accuracy and its performance. If  $\tau$  is too large, the simulation is fast but less accurate, if it is too little the simulation is slow. There is a need to write a procedure to determine the largest  $\tau$  approximately satisfying the leap condition.

##### 4.4.3.2 Negative population of reactant species

The simulation needs to make sure that the generated random number do not cause the firing of reactions to result in negative population of species.

##### 4.4.3.3 Switch to exact simulation

It needs a robust condition to switch to exact simulation when  $\tau$  is very small because the cost for generating the random numbers becomes expensive, making exact SSA more efficient.

#### 4.4.4 Leap selection

The leap selection procedure tries to determine a leap approximately satisfying the leap condition by bounding the change in propensity during the leap by an error parameter. Let  $0 < \epsilon \ll 1$  be the error parameter and  $\Delta a_j(\vec{x}) = a_j(X(t + \tau)) - a_j(X(t))$ , the change in propensity after the leap, the leap selection will select  $\tau$  such that the propensity change is bounded by the error parameter  $\epsilon$ .

##### 4.4.4.1 Postleap $\tau$ selection

The postleap selection starts with a predefined small  $\tau$  value. A trial leap is performed and the difference in propensity is computed and compared against  $\epsilon$ , checking  $|\Delta a_j(\vec{x})| \leq \epsilon$ . If this holds for all reaction  $\tau$  is accepted, if it fails it is reduced and the procedure is repeated.

**4.4.4.1.1 Issues** This procedure poses many issues: it is not robust, the starting value is dependent on the model. Moreover a lot of random numbers may be wasted during the simulation, degrading the simulation performance. Furthermore, the selection may bias infrequent reactions from large changes.

#### 4.4.4.2 Preleap $\tau$ selection

The leap selection estimates the changes in propensities of reactions. The selection of the leap can be directly through bounding changes in propensity values or through bounding changes in species population.

**4.4.4.2.1 Bounding changes in propensities** The approach determines the leap by forcing the propensity change to be bounded by a fraction of the total propensity. The condition for enforcing the leap condition is:

$$|\Delta a_j(\vec{x})| \leq \epsilon a_0(\vec{x})$$

Let  $\lambda$  be the net change vector in which each element denotes the change in population  $X_i$  of species  $S_i$  due to the firing:

$$\lambda = X(t + \tau) - \vec{x} = \sum_{j=1}^M poi(a_j(\vec{x})\tau) \vec{v}_j$$

Using the first-order Taylor expansion of  $\Delta a_j(\vec{x})$  by using the net change vector, it can be approximated as:

$$\Delta a_j(\vec{x}) \approx \lambda \cdot \nabla a_j(\vec{x}) = \sum_{i=1}^N \lambda_i \frac{da_j(\vec{x})}{dX_i}$$

Define now  $M^2$  functions such that:

$$f_{jl}(\vec{x}) = \sum_{i=1}^N \frac{da_j(\vec{x})}{dX_i} \vec{v}_{lj}$$

Where  $j, l$  run over the index set of reactions. Plugging this into the previous renaming the running index to  $l$  and rearranging the orders of summation:

$$\Delta a_j(\vec{x}) \approx \sum_{l=1}^M f_{jl}(\vec{x}) poi(a_l(\vec{x})\tau)$$

Showing that  $\Delta a_j(\vec{x})$  is a linear combination of  $M$  independent Poisson-distributed random number and denotes a random variable with mean:

$$\mathbb{E}[\Delta a_j(\vec{x})] \approx \sum_{l=1}^M f_{jl}(\vec{x}) \mathbb{E}[poi(a_l(\vec{x})\tau)] = \sum_{l=1}^M f_{jl}(\vec{x})(a_l(\vec{x})\tau)$$

And variance:

$$Var[\Delta a_j(\vec{x})] \approx \sum_{l=1}^M f_{jl}^2(\vec{x}) Var[poi(a_l(\vec{x})\tau)] = \sum_{l=1}^M f_{jl}^2 f(\vec{x})(a_l(\vec{x})\tau)$$

#### 4.4. $\tau$ -LEAPING METHOD

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Allowing to approximate the random variable, considering a conservative approximation:

$$\Delta a_j(\vec{x}) \approx \mathbb{E}[\Delta a_k(\vec{x})] + \sqrt{\text{Var}[\Delta a_j(\vec{x})]}$$

Now considering the error parameter:

$$|\mathbb{E}[\Delta a_j(\vec{x})]| + \sqrt{\text{Var}[\Delta a_j(\vec{x})]} \leq \epsilon a_0(\vec{x})$$

To satisfy this the two terms are constrained separately:

$$|\mathbb{E}[\Delta a_j(\vec{x})]| \leq \frac{\epsilon a_0(\vec{x})}{2} \quad \wedge \quad \sqrt{\text{Var}[\Delta a_j(\vec{x})]} \leq \frac{\epsilon a_0(\vec{x})}{2}$$

Ensuring the constraint. The scaling factor  $\frac{1}{2}$  is a tunable parameter. The largest  $\tau$  that satisfies the leap condition is:

$$\tau = \min_{j=1}^M \left( \frac{\epsilon a_0(\vec{x})}{2|\mu_j|}, \frac{(\epsilon a_0(\vec{x}))^2}{4\sigma_j^2} \right)$$

Where:

$$\mu_j(\vec{x}) = \sum_{l=1}^M f_{jl}(\vec{x}) a_l(\vec{x}) = \sum_{l=1}^M \sum_{i=1}^N \frac{da_j(\vec{x})}{dX_i} \vec{v}_{li} a_l(\vec{x})$$

And:

$$\sigma_j^2(\vec{x}) = \sum_{l=1}^M f_{jl}^2(\vec{x}) a_l(\vec{x}) = \sum_{l=1}^M \sum_{i=1}^N -i = 1^N \left( \frac{da_j(\vec{x})}{dX_i} \vec{v}_{li} \right)^2 a_l(\vec{x})$$

**4.4.4.2.2 Bounding changes in species population** The bounding changes in propensities is refined in this method: although  $a_0(\vec{x})$  does limit the change in propensity, it might produce less accurate  $\tau$ . Moreover the need to evaluate  $M^2$  partial derivative is removed. The  $\tau$ -selection bounds the change in propensity  $\Delta a_j(\vec{x})$  of each  $R_j$  by its current  $a_j(\vec{x})$  instead of the total. The condition  $|\Delta a_j(\vec{x})| \leq \epsilon a_j(\vec{x})$  when  $a_j$  approaches 0, forces the leap time to be zero, halting the simulation. A minimum amount of changes in propensity of each reaction is enforced, observing that propensity changes only by discrete amounts. For  $R_j$  the minimum amount of change can be selected to be rate constant  $c_j$ , so the leap condition is written as:

$$|\Delta a_j(\vec{x})| \leq \max\{\epsilon a_j(\vec{x}), c_j\}$$

Moreover instead of directly enforcing the leap condition, the change in the population is bound such that if the change in the population of a species is bounded, then the change in propensity of the corresponding reaction given by the previous condition is satisfied, implying that it is not needed to evaluate the  $M^2$  partial derivatives. Let  $\Delta X_i = X_i(t + \tau) - X_i(t)$  be the change in the population of  $S_i$  after the leap. The  $\tau$  selection bounds the population change such that:

$$|\Delta X_i| \leq \max\{\epsilon_i X_i, 1\}$$

Where  $\epsilon_i$  is dependent from  $\epsilon$  and  $X_i(t)$  such that the equation is satisfied and the change in propensity is approximately satisfied, enforcing the leap condition.

#### 4.4. $\tau$ -LEAPING METHOD

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**4.4.4.2.2.1 Unimolecular reaction** For a unimolecular reaction  $a_j = c_j X_i$  and the propensity change is  $\Delta a_j = c_j \Delta X_i$ . The relative change in propensity is:

$$\frac{\Delta a_j}{a_j} = \frac{\Delta X_i}{X_i}$$

If the relative change in population  $S_i$  is bounded by  $\epsilon_i = \epsilon$ , the relative change in propensity of  $R_j$  is bounded by  $\epsilon$ .

**4.4.4.2.2.2 Bimolecular reaction** For a bimolecular reaction  $a_j = c_j X_i X_k$ , and the change in propensity can be approximated as:

$$\Delta a_j \approx c_j X_i \Delta X_k + c_j X_k \Delta X_i$$

So the relative change in propensity:

$$\frac{\Delta a_j}{a_j} \approx \frac{\Delta X_i}{X_i} + \frac{\Delta X_j}{X_k}$$

The relative change in population of  $S_j$  is bounded by  $\epsilon_j = \frac{\epsilon}{2}$  with  $j = i, k$ , the relative change in propensity of  $R_j$  is bounded by  $\epsilon$ .

**4.4.4.2.2.3 Dimerization reaction** For a dimerization reaction  $a_j = \frac{1}{2}c_j X_i(X_i - 1)$ . The change in propensity:

$$\Delta a_j \approx \frac{1}{2}c_j(X_i - 1)\Delta X_i + \frac{1}{2}c_j X_i \Delta X_i$$

And the relative change in propensity:

$$\frac{\Delta a_j}{a_j} \approx \frac{\Delta X_i}{X_i} + \frac{\Delta X_i}{X_i - 1} = \frac{\Delta X_i}{X_i} \left( 2 + \frac{1}{X_i - 1} \right)$$

If the relative change in population is bounded by  $\epsilon_i = \frac{\epsilon}{g}$  with  $g = \frac{2+1}{X_i - 1}$ , the relative change in propensity of the reaction will be bounded by  $\epsilon$ .

**4.4.4.2.2.4 Approximating the change in population** Knowing  $\epsilon_i$ , the last step is approximating  $\Delta X_i$  by knowing the net change in population of species:

$$\Delta X_i = \lambda_i = \sum_{j=1}^M \text{poi}(a_j(\vec{x})\tau) \vec{v}_{ji}$$

Substituting this into the leap condition and bounding the expected value and variance of  $\Delta X_i$ , the largest  $\tau$  that satisfies the leap condition is:

$$\tau = \min_{i=1}^N \left( \frac{\max\{\epsilon_i X_i, 1\}}{2|\hat{\mu}_i(\vec{x})|}, \frac{\max\{\epsilon_i X_i, 1\}^2}{4\hat{\sigma}_i^2(\vec{x})} \right)$$

Where:

$$\hat{\mu}_i(\vec{x}) = \sum_{j=1}^M \vec{v}_{ji} a_j(\vec{x}) \quad \wedge \quad \hat{\sigma}_i^2(\vec{x}) = \sum_{j=1}^M v_{ij}^2 a_j(\vec{x})$$

#### 4.4.5 Avoiding the negative population problem

The number of firings  $k_j$  follows a Poisson distribution that could lead to negative population of reactants. This could be due to two situations.

##### 4.4.5.1 The number of firings is greater than the current population of reactants

$k_j$  could be greater than the current population of reactants because  $k_j$  is unbounded.

##### 4.4.5.2 Simultaneous firing of multiple reactions

Although the population of  $S_i$  could be greater than  $k_j$ , it could be that  $S_i$  is a common reactant and the total number of firings of reactions sharing it could be greater than the population.

##### 4.4.5.3 Handling the negative population problem

A simple strategy to handle this problem is to monitor the population of each species and each time there is a species whose population is negative a flag is set and the current leap is rejected and the simulation is rolled back. A new leap trial is performed with a smaller leap value  $\alpha\tau$  where  $\alpha$  is a reduction factor. This process is repeated until no negative populations are found.

#### 4.4.6 Switching to exact simulation

If  $\tau$  is smaller than a few multiple of  $\frac{1}{a_0(\vec{x})}$ , the expected time to the firing of the next reaction in the exact simulation, it is likely that only some of the  $k_j$  are 1, while the others are 0. This method than gains little over the exact strategy, so it is better to use exact SSA. TO handle this case let  $k$  be an integer denoting a multiplicative factor of the expected time to the firing of a reaction and  $p$  the number of exact SSA steps performed.  $\frac{k}{a_0(\vec{x})}$  is defined as threshold for switching to exact SSA, performing  $p$  exact steps if  $\tau$  is smaller than the threshold before trying a new leap.

#### 4.4.7 The $\tau$ -leaping algorithm

An implementation of the  $\tau$ -leaping method can be found in algorithm 28

#### 4.4. $\tau$ -LEAPING METHOD

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**Algorithm 28:**  $\tau$ -leaping method()

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```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$ , the error control parameter  

    $0 < \epsilon \ll 1$ , the reduction factor  $\alpha < 1$ , the threshold parameter  $k$  and the exact number of  

   exact SSA steps parameter  $p$ 
2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$ 
3  $t = 0$ 
4  $\vec{X} = \vec{x}_0$ 
5  $a_0 = 0$ 
6 foreach  $R_j \in Reactions$  do
7   compute  $a_j$ 
8    $a_0 = a_0 + a_j$ 
9 while  $t < T_{\max}$  do
10   $threshold = \frac{k}{a_0}$ 
11  determine  $\tau$  satisfying the leap condition with one of the leap selection procedures
12   $acceptedLeap = \text{false}$ 
13  repeat
14     $acceptedLeap = \text{true}$ 
15    if  $\tau > threshold$  then
16      generate  $M$  Poisson-distributed random numbers  $k_j \sim poi(a_j(\vec{x})\tau)$ 
17       $X = X + \sum_{j=1}^M k_j \vec{v}_j$ 
18       $t = t + \tau$ 
19    else
20      perform  $p$  SSA simulation steps
21    if  $\exists a$  species in  $X$  whose population  $X_i < 0$  then
22      roll back state  $X = X - \sum_{j=1}^M k_j \vec{v}_j$  and time  $t = t - \tau$ 
23       $\tau = \alpha\tau$ 
24       $acceptedLeap = \text{false}$ 
25  until  $acceptedLeap$ 

```

---

#### 4.4.8 Improvements for $\tau$ -leaping

##### 4.4.8.1 Modified $\tau$ -leaping

The modified  $\tau$ -leaping method efficiently handles the negative population problem. If the population of a species is low, the probability that it becomes negative is higher when reaction involving it fire. During the simulation, the reaction involving the low population species will be marked as critical reaction and monitored because their reactant species are likely to be exhausted.

**4.4.8.1.1 Permitted firings** Let  $L_j$  be the number of permitted firings of  $R_j$  during  $\tau$ .  $L_j$  depends on the reactants of  $R_j$ , but it is difficult to determine because the population of them

#### 4.4. $\tau$ -LEAPING METHOD

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can change due to other reactions. This methods estimate  $L_i$  by assuming that the reactant of reactions are independent during the simulation. In this way the maximum number of permitted firings of  $R_j$  involving  $S_i$  is equal to the population of  $S_i$  divided by its stoichiometric coefficient  $v_{ji}^0$ . The minimum of these value will give the maximum number of permitted firings:

$$L_j = \min_{S_i \in Reactants} \left[ \frac{X_i}{v_{ij}^-} \right]$$

Where  $[ - ]$  is the truncation operator.

**4.4.8.1.2 Critical reactions** Let  $n_c$  be the critical value for classifying reactions. The reaction set is partitioned into the critical reaction set  $\mathcal{R}^c$  and the non critical one  $\mathcal{R}^{nc}$ .  $\mathcal{R}^c$  contains reactions with  $L_j \leq n_c$  and  $\mathcal{R}^{nc}$  the rest:

$$\mathcal{R}^x = \{R_j | L_j \leq n_c\} \quad \wedge \quad \mathcal{R}^{nc} = \{R_j | L_j > n_c\}$$

The partition has to be updated regularly because  $L_j$  changes after every reaction firing.

**4.4.8.1.3 Firing of reactions** The firing of reaction in  $\mathcal{R}^c$  is done through SSA, while  $\mathcal{R}^{nc}$  with  $\tau$ -leaping. Let  $\tau^{nc}$  be the largest time that satisfies the leap condition for reaction in  $\mathcal{R}^{nc}$  and  $\tau^c$  the next firing time of a reaction in  $\mathcal{R}^c$ . The actual leap time will be:

$$\tau = \min(\tau^{nc}, \tau^c)$$

Because at most one reaction in  $\mathcal{R}^c$  is allowed to fire in the leap so that the population of their species never becomes negative.

**4.4.8.1.4 algorithm** The modified  $t$ -leaping method is outlined in algorithm 29.

#### 4.4. $\tau$ -LEAPING METHOD

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**Algorithm 29:** Modified  $\tau$ -leaping method()

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**1 Input:** a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$ , the error control parameter  $0 < \epsilon \ll 1$ , the reduction factor  $\alpha < 1$ , the threshold parameter  $k$  and the exact number of exact SSA steps parameter  $p$ , the critical value  $n_c$

**2 Output:** a trajectory of the biochemical reaction network, which is a collection of states  $X(t)$  for time  $0 \leq t \leq T_{\max}$

**3**  $t = 0$

**4**  $\vec{X} = \vec{x}_0$

**5 while**  $t < T_{\max}$  **do**

**6**    $a_0 = 0$

**7 foreach**  $R_j \in Reactions$  **do**

**8**     compute  $a_j$

**9**      $a_0 = a_0 + a_j$

**10** compute  $L_j$  for every reaction  $R_j$

**11** partition reaction into critical  $\mathcal{R}^c$  and non-critical  $\mathcal{R}^{nc}$  according to  $n_c$ ; determine leap time  $\tau^{nc}$  satisfying the leap condition for  $\mathcal{R}^{nc}$

**12**  $threshold = \frac{k}{a_0}$

**13**  $acceptedLeap = \text{false}$

**14 repeat**

**15**    $acceptedLeap = \text{true}$

**16**   **if**  $\tau^{nc} > threshold$  **then**

**17**     compute the firing time  $\tau^c$  of the next reaction in  $\mathcal{R}^c$  according to SSA

**18**      $\tau = \min(\tau^{nc}, \tau^c)$

**19**     **foreach**  $R_j \in Reactions$  **do**

**20**       **if**  $R_j \in \mathcal{R}^{nc}$  **then**

**21**         generate Poisson-distributed random number  $k_j \sim poi(a_j(\vec{x})\tau)$

**22**       **if**  $R_j \in \mathcal{R}^c$  **then**

**23**          $k_j = 0$

**24**       **if**  $\tau^{nc} > \tau^c$  **then**

**25**         select reaction firing  $R_\mu \in \mathcal{R}^c$  by SSA and set  $k_\mu = 1$

**26**       generate  $M$  Poisson-distributed random numbers  $k_j \sim poi(a_j(\vec{x})\tau)$

**27**        $X = X + \sum_{j=1}^M k_j \vec{v}_j$

**28**        $t = t + \tau$

**29**     **else**

**30**       perform  $p$  SSA simulation steps for all reactions

**31**     **if**  $\exists S_i \in X, X_i < 0$  **then**

**32**       roll back state  $X = X - \sum_{j=1}^M k_j \vec{v}_j$  and time  $t = t - \tau$

**33**        $\tau = \alpha\tau$

**34**        $acceptedLeap = \text{false}$

**35**     **until**  $acceptedLeap$

---

**4.4.8.1.5 Discussion** A non-critical reaction could achieve a negative population, so there is still a need to check it and roll back when necessary, but the frequency is decreased and is controlled through  $n_c$ . If  $n_c \rightarrow \infty$  the modified  $\tau$ -leaping converges to SSA, while if  $n_c = 0$  it converges to the original  $\tau$ -leaping.

#### 4.4.8.2 Binomial $\tau$ -leaping

In binomial  $\tau$ -leaping the Poisson-distributed random number are approximated with a binomial-distributed one. Let  $k_j$  be the number of firing of a reaction given  $\tau$  and  $L_j$  the maximum number of permitted firings. The negative population problem is avoided if  $k_j \leq L_j$ , a requirement that can be guaranteed by the binomial distribution.

**4.4.8.2.1 The binomial distribution** The number of firings during a leap is approximated as a series of  $L_j$  trials such that the probability that  $R_j$  fires during a trial is:

$$p_j = \frac{a_j(\vec{x})\tau}{L_j}$$

And the rejection probability is  $1 - p_j$ . The number of firings follows a binomial distribution  $k_j \sim \text{bin}(p, L_j)$ . This bounds  $R_j$  to not fire more than  $L_j$  times.

**4.4.8.2.2 Species involved in many reactions** This does not resolve the negative population problem because a reactant species may be involved in many reactions. To solve the problem and additional N-vector  $\tilde{X}$  is used to track the population of reactants of reactions during a leap. At time  $t$  set  $\tilde{X}(t) = X(t)$ , each time a reaction fire  $\tilde{X}(t)$  updates the population of its reactants: let  $\vec{v}_j^-$  be the change in population of reactants by the firing of  $R_j$ ,  $\tilde{X} = \tilde{X} - k_j \vec{v}_j^-$ . The maximum number of permitted firing of the next reaction is updated to reflect the change:

$$L_j = \min_{S_i \in \text{reactants}(R_j)} \left[ \frac{\tilde{X}_i}{v_{ji}^-} \right]$$

**4.4.8.2.3 Algorithm** An implementation of the binomial  $\tau$ -leaping method is outlined in algorithm 30

#### 4.4. $\tau$ -LEAPING METHOD

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**Algorithm 30:** Binomial  $\tau$ -leaping method()

---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$ , the error control parameter  

    $0 < \epsilon \ll 1$ , the reduction factor  $\alpha < 1$ , the threshold parameter  $k$  and the exact number of  

   exact SSA steps parameter  $p$ 
2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$ 
3  $t = 0$ 
4  $\tilde{X} = \vec{x}_0$ 
5 while  $t < T_{\max}$  do
6    $a_0 = 0$ 
7   foreach  $R_j \in Reactions$  do
8     compute  $a_j$ 
9      $a_0 = a_0 + a_j$ 
10  determine  $\tau$  satisfying the leap condition
11   $threshold = \frac{k}{a_0}$ 
12  if  $\tau^{nc} > threshold$  then
13     $\tilde{X} = X$ 
14    foreach  $R_j \in Reactions$  do
15      compute  $L_j$  for reaction  $R_j$  using  $\tilde{X}$ 
16       $p_j = \frac{a_j \tau}{L_j}$ 
17      generate binomial distributed random number  $k_j \sim bin(P_j, L_j)$ 
18       $\tilde{X} = \tilde{X} + k_j \vec{v}_j$ 
19       $X = X + \sum_{j=1}^M k_j \vec{v}_j$ 
20     $t = t + \tau$ 
21  else
22    perform  $p$  SSA simulation steps for all reactions

```

---

**4.4.8.2.4 Discussion** This method imposes some constraint on the simulation: the leap time is restricted such that  $\tau < \frac{L_j}{a_j(\vec{x})}$ . Moreover the expected  $k_j$  is the same as the Poisson distribution, but the variance is smaller than the Poisson one:

$$Var[bin(p_j, L_j)] = a_j(\vec{x})\tau \left[ 1 - \frac{a_j(\vec{x})\tau}{L_j} \right]$$

Finally the order of execution of reactions depends on the current availability of reactants and affects the variance of  $k_j$ , biasing the trajectories. To limit the bias the order of execution could be chosen randomly.

#### 4.4.8.3 Implicit $\tau$ -leaping

In the implicit  $\tau$ -leaping method performance are improved for biochemical reactions with highly diverse reaction rates. The leap time is very small, yielding a small number of firings of each reaction

#### 4.4. $\tau$ -LEAPING METHOD

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in a leap, degrading simulation efficiency. This is improved by allowing to choose an arbitrary large  $\tau$  value through an implicit approximation form.

**4.4.8.3.1 Correction term** The state update formula is complemented with a correction term to account for the change in propensity of each reaction over  $[t, t + \tau]$ . If the propensity of a reaction changes after the leap, the number of firing is changed accordingly. So  $k_j$  is the sum of  $poi(a_j(\vec{x})\tau)$  and the second part is a zero-mean random variable  $[a_j(X(t + \tau)) - a_j(\vec{x})]\tau$ . The propensity  $a_j(X(t + \tau))$  in the correction part is a function of the unknown random state, the number of firing during the leap is:

$$k_j = poi(a_j(\vec{x})\tau) + [a_j(X(t + \tau)) - a_j(\vec{x})]\tau$$

And the state update becomes:

$$X(t + \tau) = \vec{x} + \sum_{j=1}^M (poi(a_j(\vec{x})\tau) + [a_j(X(t + \tau)) - a_j(\vec{x})]\tau) \vec{v}_j$$

A root finding method like the Newton-Raphson can be applied to find the next state and the population of species in the unknown vector has to be cast to the nearest integer.

**4.4.8.3.2 Algorithm** An implementation of the implicit  $\tau$ -leaping method is outlined in algorithm 31.

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**Algorithm 31: Implicit  $\tau$ -leaping method()**

---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$  and the leap  $\tau$   

2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$   

3  $t = 0$   

4  $\vec{X} = \vec{x}_0$   

5 choose a leap  $\tau$  value  

6 while  $t < T_{\max}$  do  

7    $a_0 = 0$   

8   foreach  $R_j \in Reactions$  do  

9     compute  $a_j$   

10     $a_0 = a_0 + a_j$   

11   generate  $M$  Poisson distributed random number  $k_j \sim poi(a_j\tau)$   

12    $X(t + \tau) = \vec{x} + \sum_{j=1}^M (k_j + [a_j(X(t + \tau)) - a_j]\tau) \vec{v}_j$   

13    $t = t + \tau$ 

```

---

**4.4.8.3.3 Discussion** Since  $\tau$  is fixed it is a time-stepping algorithm. The grate efficiency is achieved from being able to choose a large leap for each leap. This tends to dampen fluctuation of species. To solve this downshifting could be employed: the  $\tau$  leap is interfaced with a sequence of smaller steps simulated using SSA to retain the damped fluctuation while still achieving the computational efficiency of the implicit approach.

## 4.5 $k_\alpha$ -leaping method

The  $K_\alpha$ -leaping method is a variant of  $\tau$  leaping. It leaps down by a predetermined number of firing for a predetermined  $R_\alpha$  and may be more convenient in some circumstance. Let  $k_\alpha$  be the number of firing of  $R_\alpha$  given  $X(t) = \vec{x}$ . Let  $\tau$  be the length so that at  $t + \tau$  the  $k_\alpha$ th firing of  $R_\alpha$  occurs. This method assumes that the leap condition is satisfied for all reactions in  $[t, t + \tau]$ . The number of firings  $k_j$  for  $R_j$ ,  $j \neq \alpha$  in the time interval still follows  $poi(a_j(\vec{x})\tau)$ .

### 4.5.1 Computing the time length

To compute  $\tau$  consider  $R_\alpha$  at time  $t$ . Each firing of  $R_j$  is an exponentially distributed random number  $exp(a_\alpha(x))$ .  $\tau$  in which there are  $k_\alpha$  firing of  $R_\alpha$  is the sum of  $k_\alpha$  exponential distribution with the same rate  $exp(a_\alpha(x))$ . So the time length  $\tau$  is an Erlang random number  $erlang(k_\alpha, a_\alpha)$  with shape  $k_\alpha$  and rate  $a_\alpha$ .

### 4.5.2 Selecting the number of firings

To select the largest  $k_\alpha$  satisfying the leap condition a control parameter  $0 < \epsilon \ll 1$  is used. Let  $\tau^{temp}$  be the largest time selected by the  $\tau$  selection procedure.  $k_\alpha \sim poi(a_\alpha(\vec{x})\tau^{temp})$ , so the average number of firing is:

$$k_\alpha = [a_\alpha(\vec{x})\tau^{temp}]$$

Where  $[-]$  is the truncation operator.  $k_\alpha$  is then used for the simulation and  $\tau^{temp}$  is discarded.

### 4.5.3 Algorithm

An implementation of the  $k_\alpha$  leaping method is outlined in algorithm 32.

## 4.5. $K_\alpha$ -LEAPING METHOD

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**Algorithm 32:**  $k_\alpha$ -leaping method()

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**1 Input:** a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$ , the error control parameter  $0 < \epsilon \ll 1$

**2 Output:** a trajectory of the biochemical reaction network, which is a collection of states  $X(t)$  for time  $0 \leq t \leq T_{\max}$

**3**  $t = 0$

**4**  $\vec{X} = \vec{x}_0$

**5** **while**  $t < T_{\max}$  **do**

**6**     $acceptedLeap = \text{false}$

**7**    **repeat**

**8**      $acceptedLeap = \text{true}$

**9**     compute  $a_j$  for each  $R_j$

**10**    determine  $k_\alpha$  satisfying the leap condition

**11**    generate  $\tau \sim erlang(k_\alpha, a_\alpha)$

**12**    **foreach**  $R_j, j \neq \alpha$  **do**

└ generate Poisson-distributed random numbers  $k_j \sim poi(a_j(\vec{x})\tau)$

**14**     $X = X + \sum_{j=1}^M k_j \vec{v}_j$

**15**     $t = t + \tau$

**16**    **if**  $\exists$  a species in  $X$  whose population  $X_i < 0$  **then**

**17**     roll back state  $X = X - \sum_{j=1}^M k_j \vec{v}_j$  and time  $t = t - \tau$

**18**     reduce  $k_\alpha$

**19**      $acceptedLeap = \text{false}$

**20**    **until**  $acceptedLeap$

---

### 4.5.4 Discussion

This method has the same performance as  $\tau$ -leaping, but it provides a more flexible way to choose the reaction and to adjust its number of firings to enforce the leap condition. In particular if  $R_\alpha$  is selected such that  $a_\alpha = \max_{j=1}^M a_j$  and bounds  $k_\alpha$  to an upper value, the number of firings of the other reactions are bounded by this, making the leap condition easier to enforce by tuning this bound.

### 4.5.5 K-leaping method

The  $K$ -leaping method or  $R$ -leaping method is a generalization of the  $k_\alpha$ -leaping. It leaps down the simulation by total  $K$  firings of reactions chosen satisfying the leap condition. Let  $\tau$  be the time length to that there are  $K$  reaction firings in  $[t, t + \tau]$ , given  $X(t) = \vec{x}$ . The firing time of a reaction is  $\exp(a_0)$ ,  $\tau$  is the sum of  $K$  exponential distribution with rate  $a_0$  and so is  $erlang(K, a_0(\vec{x}))$ .

#### 4.5.5.1 Number of firing

Let  $\mathbb{P}\{k_1, \dots, k_M | K, \tau, \vec{x}, t\}$  be the joint probability that there are  $k_j$  firings for each  $R_j$  given the  $X(t) = \vec{x}$ . The explicit formula under the leap assumption can be derived considering that the probability that  $R_j$  fires in the interval is:

$$p_j = \frac{a_j}{a_0}$$

Moreover:

$$\sum_{j=1}^M k_j = K$$

The joint probability is then a multinomial distribution  $multi(K, p_1, \dots, p_M)$ , with formula:

$$\mathbb{P}\{k_1, \dots, k_M | K, \tau, \vec{x}, t\} = \frac{K!}{k_1! \cdots k_M!} p_1^{k_1} \cdots p_M^{k_M}$$

The number of firings is obtained by sampling  $multi(K, p_1, \dots, p_M)$ .

#### 4.5.5.2 Selecting $\mathbf{K}$

To select the largest  $K$  satiating the leap condition with control parameter  $0 < \epsilon \ll 1$ , consider the preleap selection whit bounding  $\Delta a_j(\vec{x}) \leq \epsilon a_0(\vec{x})$ . The expected value and variance can be obtained using the properties of the multinomial distribution:

- $\mathbb{E}[k_j] = Kp_j = \frac{Ka_j(\vec{x})}{a_0(\vec{x})}$ .
- $Var[k_j] = Kp_j(1 - p_j) = \frac{Ka_j(\vec{x})}{a_0(\vec{x})} \left(1 - \frac{a_j(\vec{x})}{a_0(\vec{x})}\right)$ .
- $cov(k_j, k_m) = -Kp_j p_m = -\frac{Ka_j(\vec{x}) a_m(\vec{x})}{a_0^2(\vec{x})}$ .

Therefore:

$$\mathbb{E}[\Delta a_j(\vec{x})] \approx \sum_{l=1}^M f_{jl}(\vec{x}) \mathbb{E}[k_l] = K \frac{\mu_j(\vec{x})}{a_0(\vec{x})}$$

And:

$$\begin{aligned} Var[\Delta a_j(\vec{x})] &\approx \sum_{l=1}^M f_{jl}^2(\vec{x}) Var[k_l] + \sum_{l=1}^M \sum_{l'=1}^M f_{jl}(\vec{x}) f_{jl'}(\vec{x}) cov(k_l, k_{l'}) = \\ &= K \left( \frac{\sigma_j^2(\vec{x})}{a_0(\vec{x})} - \frac{\mu_j^2(\vec{x})}{a_0^2(\vec{x})} \right) \end{aligned}$$

Where  $\mu_j(\vec{x})$  and  $\sigma_j^2$  are defined as in the preleap selection for the  $\tau$ -leaping method. The largest  $K$  is then;

$$K = \left[ a_0(\vec{x}) \min_{k=1}^M \left( \frac{\epsilon a_0(\vec{x})}{2|\mu_j(\vec{x})|}, \frac{(\epsilon a_0(\vec{x}))^2}{4(\sigma_j^2(\vec{x}) - \frac{\mu_j^2(\vec{x})}{a_0(\vec{x})})} \right) \right]$$

Where  $[ - ]$  is the truncation operator.

## 4.5. $K_\alpha$ -LEAPING METHOD

---

### 4.5.5.3 Algorithm

An implementation of the  $K$ -leaping method is found in algorithm 33.

---

#### Algorithm 33: $K$ -leaping method()

---

```

1 Input: a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  

    $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the  

   initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$ , the error control parameter  

    $0 < \epsilon \ll 1$ 
2 Output: a trajectory of the biochemical reaction network, which is a collection of states  

    $X(t)$  for time  $0 \leq t \leq T_{\max}$ 
3  $t = 0$ 
4  $\vec{X} = \vec{x}_0$ 
5 while  $t < T_{\max}$  do
6    $acceptedLeap = \text{false}$ 
7   repeat
8      $acceptedLeap = \text{true}$ 
9     compute  $a_j$  for each  $R_j$ 
10     $a_0 = \sum_{j=1}^M a_j$ 
11    determine  $K$  satisfying the leap condition
12    generate  $\tau \sim erlang(k_\alpha, a_\alpha)$ 
13     $p_j = \frac{a_j}{a_0} \forall j = 1, \dots, M$ 
14    generate  $k_j \sim multi(K, p_1, \dots, p_M) \forall j = 1, \dots, M$ 
15     $X = X + \sum_{j=1}^M k_j \vec{v}_j$ 
16     $t = t + \tau$ 
17    if  $\exists a$  species in  $X$  whose population  $X_i < 0$  then
18      roll back state  $X = X - \sum_{j=1}^M k_j \vec{v}_j$  and time  $t = t - \tau$ 
19      reduce  $K$ 
20       $acceptedLeap = \text{false}$ 
21  until  $acceptedLeap$ 
```

---

### 4.5.5.4 Discussion

The  $K$ -leaping differs from the  $k_\alpha$  method in two points:

- $\tau$  is generated from  $erlang(K, a_0)$ .
- $k_j \sim multi(K, p_1, \dots, p_m)$  with  $p_j = \frac{a_j}{a_0}$

This method handles the negative population easier than  $\tau$ -leaping, improving the accuracy.  $K$  is a deterministic number and represent an upper bound on the number of firings on each reaction. If the negative population problem happens, decreasing the  $K$  reduces the change of it.

## 4.6 Chemical Langevin method

The chemical Langevin method is an approximation of the  $\tau$ -leaping. Let  $\tau$  be the time satisfying the leap condition.  $k_j$  of  $R_j$  in the leap follows  $poi(a_j(\vec{x})\tau)$ . Assume that the expected value of the Poisson distribution is large enough. CLE assumes that there exists a small  $\tau > 0$  such that the change in propensity for each  $R_j$  during  $[t, t + \tau]$  is negligibly small and:

$$a(\vec{x})\tau \gg 1$$

Now  $poi(a_j(\vec{x})\tau)$  can be approximated to a normal distribution with same mean and variance:

$$poi(a_j(\vec{x})\tau) \approx norm(a_j(\vec{x})\tau, a_j(\vec{x})\tau) = a_j(\vec{x})\tau + \sqrt{a_j(\vec{x})\tau} norm(0, 1)$$

### 4.6.1 State update

The state update after the leap is approximated by:

$$\begin{aligned} X(t + \tau) &\approx \vec{x} + \sum_{j=1}^M poi(a_j(\vec{x})\tau)\vec{v}_j \approx \\ &\approx \vec{x} + \sum_{j=1}^M a_j(\vec{x})\vec{v}_j\tau + \sum_{j=1}^M \sqrt{a_j(\vec{x})\tau} norm(0, 1)\vec{v}_j \end{aligned}$$

This is the chemical Langevin equation CLE. The state is no longer an integer vector due to the square root.

### 4.6.2 Algorithm

An implementation of the CLE is outlined in algorithm 34.

---

**Algorithm 34: Chemical Langevin method (CLE)()**

---

- 1 **Input:** a biochemical reaction network of  $M$  reactions in which each reaction  $R_j$ ,  $j = 1, \dots, M$  is accompanied with the state change vector  $\vec{v}_j$  and the propensity  $a_j$ , the initial state  $\vec{x}_0$  at time 0 and the simulation ending time  $T_{\max}$ , the error control parameter  $0 < \epsilon \ll 1$
  - 2 **Output:** a trajectory of the biochemical reaction network, which is a collection of states  $X(t)$  for time  $0 \leq t \leq T_{\max}$
  - 3  $t = 0$
  - 4  $\vec{X} = \vec{x}_0$
  - 5 **while**  $t < T_{\max}$  **do**
  - 6   compute  $a_j$  for each  $R_j$
  - 7   determine  $\tau$  satisfying the leap condition and  $a_j\tau \gg 1$
  - 8   generate  $M$  unit normal-distributed random number  $n_j \sim norm(0, 1)$
  - 9    $X = X + \sum_{j=1}^M a_j\tau\vec{v}_j + \sum_{j=1}^M n_j\vec{v}_j\sqrt{a_j\tau}$
  - 10    $t = t + \tau$
-

#### 4.6.3 Discussion

This method does not handle the negative population explicitly, but it is relaxed because the population of species is very large in order to satisfy the CLE assumption and can be approximated to a continuous state. The CLE method is faster because generating random normal distributed number is easier than the Poisson distribution and  $k_j \gg 1$ .

# Chapter 5

## Deterministic simulations

### 5.1 introduction

When the last noise term of equation:

$$X(t + \tau) \approx \vec{x} + \sum_{j=1}^M a_j(\vec{x}) \vec{v}_j \tau + \sum_{j=1}^M \sqrt{a_j(\vec{x}) \tau} \text{norm}(0, 1) \vec{v}_j$$

Becomes negligibly small compared with the second done, a deterministic way to computing the dynamics of a system can be applied. This happens in the limiting case  $a_j(\vec{x})\tau \rightarrow \infty$  and the deterministic simulation produces an average behaviour of the system close to the one obtained by averaging an infinite number of stochastic simulations of the system starting from the same initial state. Deterministic simulation are faster than exact stochastic ones because reaction events are executed as the simultaneous application of a set of reactions. A single run is sufficient because stochasticity of the system is not considered any more. One way to simulate a biological system according to a deterministic approach is to translate it into a set of ordinary differential equations or ODEs.

### 5.2 From biochemical reactions to ODEs

Ordinary differential equations can be used to simulate a biochemical system that satisfied the spatial homogeneity and the continuum hypothesis.

#### 5.2.1 Starting hypothesis

##### 5.2.1.1 Continuum hypothesis

A biochemical system satisfies the continuum hypothesis if the number of molecules for each species is large enough to safely approximate molecular abundances by concentrations that vary continuously.

##### 5.2.1.2 Effect of starting hypothesis

Spatial homogeneity allows to randomize spatial information: the rate of each reaction is space independent. The continuum hypothesis allows to approximate discrete changes in molecule number

## 5.2. FROM BIOCHEMICAL REACTIONS TO ODES

---

by continuous changes in concentration, moreover individual reactions are infinitesimal changes in molecule abundance. This holds for species with molecules counts of thousands or more. In the cases where molecule abundance is low, its changes will have to be treated like discrete steps in population size and stochastic simulation should be preferred.

### 5.2.2 Law of mass action

When the two hypothesis are satisfied, a biochemical reaction system can be translated into a set of ODEs by the law of mass action. The law of mass action states that the deterministic rate of a chemical reaction is proportional to the product of the concentrations of its reactants. Now let  $[A] = \frac{\#A}{N_A V}$  be the molar concentration of species  $A$  in a chemical volume  $V$  and  $N_A$  Avogadro's number. Some example of conversion of chemical reactions into ODEs are outlined in table 5.2.

Reaction type	Reaction	Rate	ODEs
Zero-order reaction	$\emptyset \xrightarrow{k} A$	$k$	$\frac{d[A]}{dt} = k$
First-order reaction	$A \xrightarrow{k} B$	$k[A]$	$\frac{d[A]}{dt} = -k[A]; \frac{d[B]}{dt} = k[A]$
Second-order reaction	$A + B \xrightarrow{k} C$	$k[A][B]$	$\frac{d[A]}{dt} = \frac{d[B]}{dt} = -k[A][B]; \frac{d[C]}{dt} = k[A][B]$
Second-order reaction same reactant	$A + A \xrightarrow{k} B$	$k[A]^2$	$\frac{d[A]}{dt} = -k[A]^2; \frac{d[B]}{dt} = k[A]^2$
Third-order reaction	$A + B + C \xrightarrow{k} D$	$k[A][B][C]$	$\frac{d[A]}{dt} = \frac{d[B]}{dt} = \frac{d[C]}{dt} = -k[A][B][C]$ $\frac{d[D]}{dt} = k[A][B][C]$

**Table 5.1:** Conversion of biochemical reactions into ODEs

Taking into consideration that the deterministic rate  $k$  is not the stochastic reaction rate constant  $c_j$  but will be computed as in table ??.

Reaction type	Reaction	Rate	Unit
Zero-order reaction	$\emptyset \xrightarrow{k} A$	$k = \frac{c}{N_A V}$	concentration · time <sup>-1</sup>
First-order reaction	$A \xrightarrow{k} B$	$k = c$	time <sup>-1</sup>
Second-order reaction	$A + B \xrightarrow{k} C$	$k = c N_A V$	concentration <sup>1</sup> time <sup>-1</sup>
Second-order reaction same reactant	$A + A \xrightarrow{k} B$	$k = \frac{c N_A V}{2}$	concentration <sup>1</sup> time <sup>-1</sup>
Third-order reaction	$A + B + C \xrightarrow{k} D$	$k = c(N_A V)^2$	concentration <sup>2</sup> time <sup>-1</sup>

**Table 5.2:** Conversion of biochemical reactions into ODEs

### 5.2.3 Building the set of ODEs

Consider now a biochemical reaction system with  $N$  species  $S_1, \dots, S_N$  interacting through  $M$  reactions  $R_1, \dots, R_M$  and a stoichiometric matrix:

$$\vec{v} = \vec{v}^+ - \vec{v}^-$$

The deterministic rate constant of each reaction is:

$$k_j = \frac{c_j (N_A V)^{Order_j - 1}}{\prod_{i=1}^N v_{ij}^{-1}!}$$

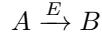
Where  $Order_j$  is the order of reaction  $R_j$ . The set of ODEs modelling the evolution of the species is:

$$\frac{d[S_i]}{dt} = \sum_{j=1}^M -j = 1^M \left( k_j \vec{v}_{ji} \prod_{l=1}^N [S_l]^{\vec{v}_{jl}} \right), \forall i = 1, \dots, N$$

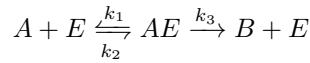
Other methods can be used to approach this translation like the Michaelis-Menten kinetics or the Hill kinetics. The former can be used to quantify cooperative binding, the phenomena of binding of a ligand to a macromolecule enhancing when another molecule is attached to the same macro-one.

#### 5.2.4 Michaelis-Menten kinetics

Michaelis-Menten (MM) kinetics are used to model enzymatic reactions:



Enzyme accelerate the reaction, and to transform this reaction into a law of mass action it needs to be expanded into:



Describing the process more accurately. The translation to a set of ODE of the reaction requires the definition of four differential equation, where also  $[E]$  and  $[EA]$  are considered. The MM kinetics allow to simplify the model by reducing the number of equation, so the equation is translated into two odes considering the variation of concentration of  $A$  and  $B$ :

$$\frac{d[A]}{dt} = -\frac{d[B]}{dt} = -V_{MAX} \frac{[A]}{K_M + [A]}$$

Where:

- $V_{MAX}$  is the maximum velocity of the enzymatic reaction.
- $K_M$ , Michaelis constant, is the concentration of the substrate at which the reaction rate is half of its maximum.

The effect of the enzyme is modelled, where:

$$K_M = \frac{k_2 + k_3}{k_1} \quad \wedge \quad V_{MAX} = k_{cat}[E_T]$$

Where  $[E_T]$  is the enzyme available to the system. This kinetics can be used also in the context of stochastic simulation, so that the propensity for this type of reactions will be:

$$a(\vec{x}) = \frac{V_{MAX} A}{K_M + A}$$

Where  $V_{MAX}$  and  $K_M$  are scaled to consider molecule abundances.

### 5.3 Numerical solution of ODEs

The simulation of a system of ODE is addressed by solving the initial value or Cauchy problem. This corresponds to finding the solution of a set of differential equations that satisfies the initial condition corresponding to the initial concentration of the species. An exact solution is usually too complex, so suitable numerical methods need to be used. This will produce approximations of the solution at specified time points. Some interpolation methods can be used to obtain intermediate values. Even when an exact solution is found, the dynamics of the biochemical system is an approximation.

#### 5.3.1 Finding a solution

Consider the system with  $N$  species:

$$\frac{d[X]}{dt} = \vec{F}(t, [X])$$

Where:

- $\vec{F} : \mathbb{R} \times \mathbb{R}^N \rightarrow \mathbb{R}^N$  is the vector of  $N$  functions providing the time derivatives of species concentration.
- $[X]$  is the current state of the system expressed in molecular concentrations.

Let  $I = (0, T_{\max})$  be the integration interval of the system and:

$$t_n = nh, h > 0 \wedge n = 0, \dots, N_h$$

Be the sequence of discretization of  $I$  into subintervals  $I_n = [t_n, t_{n+1}]$ , where:

- $N_h$  is the maximum integer such that  $t_{N_h} \leq T_{\max}$ .
- $h$  is the discretization stepsize.

Numerical methods compute a sequence of states  $[X_n]$ . Approximating the trajectory in terms of concentrations along the time steps starting from  $[X_0]$ . These methods can be explicit or implicit. They are called explicit if  $[X_{n+1}]$  can be computed directly from the previous state  $[X_n]$ . They are called implicit if  $[X_{n+1}]$  depends implicitly on itself through  $\vec{F}$ .

#### 5.3.2 Forward/Backward Euler method

The Forward Euler method is an explicit method, while the backward one is an implicit. The are:

$$\text{Forward Euler: } [X_{n+1}] = [X_n] + h\vec{F}(t_n, [X_n])$$

$$\text{Backward Euler: } [X_{n+1}] = [X_n] + h\vec{F}(t_{n+1}, [X_{n+1}])$$

Comparing this with the chemical Langevin equation, when stochasticity is negligible, the CLE reduces a forward Euler with  $\tau = h$ .

## 5.4. IMPROVING THE ACCURACY OF NUMERICAL METHODS

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### 5.3.2.1 Forward Euler algorithm

An implementation of the forward Euler algorithm is found in algorithm 35.

---

#### Algorithm 35: Forward Euler method()

- 1 **Input:** a system of ODEs  $\frac{d[X]}{dt} = \vec{F}(t, [X])$  corresponding to a biochemical reaction system, the initial state  $[X_0]$  of the system with species concentrations at time 0, the simulation ending time  $T_{\max}$  and the discretization stepsize  $h$
  - 2 **Output:** a trajectory of the biochemical system expressed in terms of molecule concentrations with discretization stepsize  $h$
  - 3  $t = 0$
  - 4  $[X] = [X_0]$
  - 5 **while**  $t < T_{\max}$  **do**
  - 6    $[X] = [X] + h \cdot \vec{f}(t, [X])$
  - 7    $t = t + h$
- 

### 5.3.2.2 Backward Euler algorithm

An implementation of the backward Euler algorithm is found in algorithm 36.

---

#### Algorithm 36: Backward Euler method()

- 1 **Input:** a system of ODEs  $\frac{d[X]}{dt} = \vec{F}(t, [X])$  corresponding to a biochemical reaction system, the initial state  $[X_0]$  of the system with species concentrations at time 0, the simulation ending time  $T_{\max}$  and the discretization stepsize  $h$
  - 2 **Output:** a trajectory of the biochemical system expressed in terms of molecule concentrations with discretization stepsize  $h$
  - 3  $t = 0$
  - 4  $[X] = [X_0]$
  - 5 **while**  $t < T_{\max}$  **do**
  - 6   estimate  $[X_{new}] = [X] + h \cdot \vec{F}(t, [X])$
  - 7    $t = t + h$
  - 8    $[X] = [X] + h \cdot \vec{f}(t, [X_{new}])$
- 

### 5.3.2.3 Discussion

Implicit methods are less intuitive because they need to compute an estimation of the state. This can be done by computing a first approximation of the next state which is used then to compute the actual one.

## 5.4 Improving the accuracy of numerical methods

The accuracy of the computation depends on the discretization stepsize and on the properties of the numerical method. The general form of one step for an explicit method is:

$$[X_{n+1}] = [X_n] + h\mathbb{F}(t_n, [X_n], \vec{F}(t_n, [X_n]))lh + h\epsilon_{n+1}(h)$$

Where:

- $n = 0, \dots, N_h$ .
- $h > 0$ .
- $\mathbb{F}$  is the increment function.
- $\epsilon_{n+1}(h)$  is the local truncation error LTE at  $t_{n+1}$  of the numerical method. This provides a measure of how distant the estimation is from the exact value.

A global truncation error is required to evaluate the accuracy of a numerical method.

#### 5.4.1 Global truncation error

Consider a numerical method with local truncation error  $\epsilon_{n+1}(h)$ . The global truncation error is:

$$\epsilon(h) = \max |\epsilon_{n+1}(h)|, n = 0, \dots, N_h$$

#### 5.4.2 Consistency of a numerical method

A numerical method with global truncation error  $\epsilon(h)$  is consistent with the initial value problem if:

$$\lim_{h \rightarrow 0} \epsilon(h) = 0$$

From now on only consistent numerical methods will be considered.

#### 5.4.3 Order of a numerical method

A numerical method with global truncation error  $\epsilon(h)$  has order  $p$  if:

$$\forall t \in ]0, T_{\max}[ : \epsilon(h) = O(h^p), h \rightarrow 0$$

A Taylor expansion shows that the forward Euler has order 1. To increase the accuracy of a simulation the discretization stepsize or increase the order of the numerical methods need to be decreased. Decreasing the discretization stepsize implies to compute more simulation steps, while increasing the method order the complexity of each step increases.

#### 5.4.4 Heun method

An example of a second order numerical method is the implicit trapezoidal or Crank-Nicolson method, which updates the system by:

$$[X_{n+1}] = [X_n] + \frac{h}{2} [\vec{F}(t_n, [X_n]) + \vec{F}(t_{n+1}, [X_{n+1}])]$$

The gain in accuracy is balanced by the increased complexity in the update formula, which requires the evaluation of two  $\vec{F}$  at each step. This can be transformed into the explicit alternative Heun method, which updates the system by:

$$[X_{n+1}] = [X_n] + \frac{h}{2} [\vec{F}(t_n, [X_n]) + \vec{F}(t_{n+1}, [X_n] + h\vec{F}(t_n, [X_n]))]$$

#### 5.4.4.1 Algorithm

An implementation of the Heun algorithm can be found in algorithm 37.

---

**Algorithm 37:** Heun method()

- 1 **Input:** a system of ODEs  $\frac{d[X]}{dt} = \vec{F}(t, [X])$  corresponding to a biochemical reaction system, the initial state  $[X_0]$  of the system with species concentrations at time 0, the simulation ending time  $T_{\max}$  and the discretization stepsize  $h$
  - 2 **Output:** a trajectory of the biochemical system expressed in terms of molecule concentrations with discretization stepsize  $h$
  - 3  $t = 0$
  - 4  $[X] = [X_0]$
  - 5 **while**  $t < T_{\max}$  **do**
  - 6      $[X] = [X] + \frac{h}{2}[\vec{F}(t, [X]) + \vec{F}(t, [X] + h\vec{F}(t, [X]))]$
  - 7      $t = t + h$
- 

#### 5.4.5 Runge-Kutta methods

The Runge-Kutta methods are a family of numerical methods that can be written as:

$$[X_{n+1}] = [X_n] + h\mathbb{F}(t_n, [X_n], h; \vec{F})$$

Where:

- $n = 0, \dots, N_h$ .
- $\mathbb{F}$  is the increment function of the method.
- $h > 0$ .

In particular:

$$\begin{aligned} \mathbb{F}(t_n, [X_n], h; \vec{F}) &= \sum_{i=1}^s b_i K_i \\ K_i &= \vec{F}(t_n + c_i h, [X_n] + h \sum_{j=1}^s a_{ij} K_j) \end{aligned}$$

With  $s$  being the number of stages of the method and  $a_{ij}$ ,  $b_i$  and  $c_i$  are suitable numbers that characterize the RK method. These method can be explicit or implicit depending on the values of  $a_{ij}$ . The Heun method is an explicit RK method, because  $a_{12}$  and  $a_{22}$  are zeros. The number of stages and the order of the methods are related: the minimum number  $s_{\min}$  required to get an explicit RK method of corresponding order is described in table ??

Order	1	2	3	4	5	6	7	8
$s_{\min}$	1	2	3	4	6	7	9	11

**Table 5.3:** RK order and  $s_{\min}$  relationship

4 is the maximum number of stages for which the order is not less than  $s_{\min}$ . For this a four-stage explicit RK method is the more convenient way to solve an initial-value problem.

## 5.5. MULTISTEP METHODS

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### 5.4.5.1 Fourth order RK method

An example of an update of a fourth order RK method is:

$$[X_{n+1}] = [X_n] + \frac{h}{6}(K_1 + 2K_2 + 2K_3 + k_4)$$

Where;

- $K_1 = \vec{F}(t_n, [X_n]).$
- $K_3 = \vec{F}(t_n + \frac{h}{2}, [X_n] + \frac{h}{2}K_2).$
- $K_2 = \vec{F}(t_n + \frac{h}{2}, [X_n] + \frac{h}{2}K_1).$
- $K_4 = \vec{F}(t_{n+1}, [X_n] + hK_3).$

This is called RK4 and is one of the most used numerical methods for deterministic simulations.

#### 5.4.5.1.1 Algorithm

An implementation of the RK4 method can be found at algorithm 38

---

##### Algorithm 38: RK4 method()

- 1 **Input:** a system of ODEs  $\frac{d[X]}{dt} = \vec{F}(t, [X])$  corresponding to a biochemical reaction system, the initial state  $[X_0]$  of the system with species concentrations at time 0, the simulation ending time  $T_{\max}$  and the discretization stepsize  $h$
  - 2 **Output:** a trajectory of the biochemical system expressed in terms of molecule concentrations with discretization stepsize  $h$
  - 3  $t = 0$
  - 4  $[X] = [X_0]$
  - 5 **while**  $t < T_{\max}$  **do**
  - 6      $K_1 = \vec{F}(t, [X])$
  - 7      $K_2 = \vec{F}(t + \frac{h}{2}, [X] + \frac{h}{2}K_1)$
  - 8      $K_3 = \vec{F}(t + \frac{h}{2}, [X] + \frac{h}{2}K_2)$
  - 9      $K_4 = \vec{F}(t + h, [X] + hK_3)$
  - 10     $[X] = [X] + \frac{h}{6}(K_1 + 2K_2 + 2K_3 + k_4)$
- 

## 5.5 Multistep methods

A numerical method for the approximation of the initial-value problem is a one step method if  $\forall n \geq 0$ , the computation of  $[X_{n+1}]$  depends only on  $[X_n]$ , otherwise the scheme is called a multistep method. Multistep (MS) schemes require one functional evaluation at each step and their accuracy can be increased at the expense of increasing the number of steps. They can be implicit or explicit and have an order of accuracy.

### 5.5.1 Linear multistep numerical method

A linear  $(s + 1)$ -step method is a multistep method whose update formula fits the scheme:

$$[X_{n+1}] = \sum_{j=0}^s a_j [X_{n-j}] + h \sum_{j=0}^s b_j \vec{F}(t_{n-j}, [X_{n-j}]) + h b_{-1} \vec{F}(t_{n+1}, [X_{n+1}])$$

Where:

- $n \geq s \geq 0$ .
- $a_j, b_j$  are numbers that characterize the

method. When  $b_{-1} = 0$  the method is explicit, otherwise implicit.

### 5.5.1.1 Midpoint method

The midpoint method is a second order, two step linear explicit method, which updates the system by:

$$[X_{n+1}] = [X_{n-1}] + 2h\vec{F}(t_n, [X_n])$$

They rely on the fact that the formula depend on some previous state of the system to increase accuracy. History dependency does not require additional functional evaluation because previous state are stored during the simulation. These reduces the simulation runtime, while increasing the complexity in space of the algorithm. The length of the time series of states that needs to be stored depends on the update formula and increases with the order.

**5.5.1.1.1 Algorithm** An implementation of the midpoint method can be found in 39

---

#### Algorithm 39: Midpoint method()

---

- 1 **Input:** a system of ODEs  $\frac{d[X]}{dt} = \vec{F}(t, [X])$  corresponding to a biochemical reaction system, the initial state  $[X_0]$  of the system with species concentrations at time 0, the simulation ending time  $T_{\max}$  and the discretization stepsize  $h$
  - 2 **Output:** a trajectory of the biochemical system expressed in terms of molecule concentrations with discretization stepsize  $h$
  - 3  $t = 0$
  - 4  $[X_{old}] = [X_0]$
  - 5  $[X] = [X_{old}] + \frac{h}{2} [\vec{F}(t, [X_{old}]) + \vec{F}(t + h, [X_{old}] + h \cdot \vec{F}(t, [X_{old}]))]$
  - 6  $t = h$
  - 7 **while**  $t < T_{\max}$  **do**
  - 8      $[X_{new}] = [X_{old}] + 2h \cdot \vec{f}(t, [X])$
  - 9      $[X_{old}] = [X]$
  - 10      $[X] = [X_{new}]$
  - 11      $t = t + h$
- 

**5.5.1.1.2 Discussion** In order to preserve the order of accuracy of the MS algorithm, the one-step method used in the preliminary phase must have at least the same order of the MS method.

### 5.5.1.2 Simpson method

The Simpson method is a two-step implicit linear model which updates the system by:

$$[X_{n+1}] = [X_{n-1}] + \frac{h}{3} [\vec{F}(t_{n-1}, [X_{n-1}]) + 4\vec{F}(t_n, [X_n]) + \vec{F}(t_{n+1}, [X_{n+1}])]$$

### 5.5.1.3 General linear multistep algorithm

An implementation of a generic  $(s + 1)$ -step method that requires a preliminary phase where a one-step method is used to compute the first  $s$  step of the simulation can be found in algorithm 40

**Algorithm 40: Linear  $(s + 1)$ -step method()**

---

```

1 Input: a system of ODEs  $\frac{d[X]}{dt} = \vec{F}(t, [X])$  corresponding to a biochemical reaction system,
the initial state  $[X_0]$  of the system with species concentrations at time 0, the simulation
ending time  $T_{\max}$  and the discretization stepsize  $h$  and the coefficient values  $a_j, b_j$ 
2 Output: a trajectory of the biochemical system expressed in terms of molecule
concentrations with discretization stepsize  $h$ 
3  $t = 0$ 
4  $[X_{old}] = [X_0]$ 
5 compute the first  $s$  steps of the dynamics by a one-step numerical method of order at least
equal to the implemented multistep method
6 while  $t < T_{\max}$  do
7   if  $b_{-1} \neq 0$  then
8     approximate  $[X_{t+h}]$ 
9      $[X] = \sum_{j=0}^s a_j [X_{n-j}] + h \sum_{j=0}^s b_j \vec{F}(t_{n-j}, [X_{n-j}]) + hb_{-1} \vec{F}(t_{n+1}, [X_{n+1}])$ 
10     $t = t + h$ 

```

---

### 5.5.2 Adams methods

Adams methods are linear multistep methods that update the system state:

$$[X_{n+1}] = [X_n] + h \sum_{j=-1}^s b_j \vec{F}(t_{n-j}, [X_{n-j}])$$

Where:

- $n \geq s \geq 0$ .
- $b_j$  are numbers that characterize the method.  $b_{-1} = 0$  implies that the

method is explicit and is called the Adams-Basforth method, when it is implicit is the Adams-Moulton method.

### 5.5.3 BDF methods

BDF methods are implicit linear multistep methods that update the system by:

$$[X_{n+1}] = \sum_{j=0}^s a_j [X_{n-j}] + hb_{-1} \vec{F}(t_{n+1}, [X_{n+1}])$$

Where:

- $n \geq s \geq 0$ .
- $a_j$  and  $b_{-1} \neq 0$  fully characterize the system.

## 5.6 Adaptive methods

Adaptive numerical methods change the discretization stepsize at each simulation step so that  $h$  remains close to the greatest value which keeps the global truncation error within a bound. They do

not set  $h$  but a threshold for a maximum value of the global truncation error. The output is a time series with time points not equally spaced. They require the implementation of an error estimator. Here one step methods are considered, particularly RK schemes.

### 5.6.1 Estimating the local truncation error

RK schemes are well suited to provide an efficient estimator of the local truncation error and to adapt the stepsize according to it. An a posteriori error estimator is used to estimate the local truncation error. This can be built in two ways:

- By comparing the output of the same RK method with two different stepsizes  $2h$  and  $h$ .
- By comparing the output of two RK methods of different order.

In both cases the error estimator computes a posteriori, after the simulation step. The first case a considerable increase of computational error is required, while the second do not by using two different RK methods with  $s$  stages of order  $p$  and  $p+1$ , which share the same set of values.

### 5.6.2 Runge-Kutta Fehlberg

The Runge-Kutta Fehlberg method of fourth order, or RK45 method updates the system as:

$$[X_{n+1}] = [X_n] + \frac{25}{216}K_1 + \frac{1408}{2565}K_3 + \frac{2187}{4104}K_4 - \frac{1}{5}K_5$$

Coupled with a fifth order RK method:

$$[\tilde{X}_{n+1}] = [X_n] + \frac{16}{135}K_1 + \frac{6656}{12825}K_3 + \frac{28561}{56430}K_4 = \frac{9}{50}K_5 + \frac{2}{55}K_6$$

$K_1, \dots, K_6$  are shared between methods and are computed as:

$$\begin{aligned} K_1 &= h\vec{F}(t_n, [X_n]) \\ K_2 &= h\vec{F}\left(t_n + \frac{h}{4}, [X_n] + \frac{1}{4}K_1\right) \\ K_3 &= h\vec{F}\left(t_n + \frac{3h}{8}, [X_n] + \frac{3}{32}K_1 + \frac{9}{32}K_2\right) \\ K_4 &= h\vec{F}\left(t_n + \frac{12h}{13}, [X_n] + \frac{1932}{2197}K_1 - \frac{7200}{2197}K_2 + \frac{7296}{2197}K_3\right) \\ K_5 &= h\vec{F}\left(t_n + h, [X_n] + \frac{439}{216}K_1 - 8K_2 + \frac{3680}{513}K_3 - \frac{845}{4104}K_4\right) \\ K_6 &= h\vec{F}\left(t_n + \frac{h}{2}, [X_n] - \frac{8}{27}K_1 + 2K_2 - \frac{3544}{2565}K_3 + \frac{1859}{4104}K_4 - \frac{11}{40}K_5\right) \end{aligned}$$

The fourth order version is used to compute the dynamics of the system, while the fifth order one is used to estimate the local truncation error:

$$\Delta_{n+1} = \frac{|[\tilde{X}_{n+1}] - [X_{n+1}]|}{h}$$

The error estimate is compared to the error threshold  $\epsilon_t$ . If it is less the local truncation error is assumed smaller than the threshold and the state is accepted, in the other case the new state is rejected and evaluated again using a smaller  $h$ . In both cases  $h$  is updated as:

$$h_{n+1} = h_n \sigma$$

$$\sigma = \left( \frac{\epsilon_t}{2\Delta_{n+1}} \right)^{\frac{1}{4}} \approx 0.84 \left( \frac{\epsilon_t}{\Delta_{n+1}} \right)^{\frac{1}{4}}$$

This is derived from  $\sigma = \left( \frac{\epsilon_t}{\Delta_{n+1}} \right)^{\frac{1}{p}}$ , defining how to update  $h$  for an adaptive one step method of order  $p$ .

### 5.6.2.1 Algorithm

An implementation of the RK45 method can be found at algorithm 41

## 5.6. ADAPTIVE METHODS

---



---

**Algorithm 41:** RK45 algorithm()

---

```

1 Input: a system of ODEs  $\frac{d[X]}{dt} = \vec{F}(t, [X])$  corresponding to a biochemical reaction system,
   the initial state  $[X_0]$  of the system with species concentrations at time 0, the simulation
   ending time  $T_{\max}$ , the initial discretization stepsize  $h_0$  and a threshold for the maximum
   local truncation error  $\epsilon_t$ 
2 Output: a trajectory of the biochemical system expressed in terms of molecule
   concentrations with discretization stepsize  $h_0$ 
3  $t = 0$ 
4  $[X] = [X_0]$ 
5  $h = h_0$ 
6 while  $t < T_{\max}$  do
7    $K_1 = h\vec{F}(t_n, [X_n])$ 
8    $K_2 = h\vec{F}\left(t_n + \frac{h}{4}, [X_n] + \frac{1}{4}K_1\right)$ 
9    $K_3 = h\vec{F}\left(t_n + \frac{3h}{8}, [X_n] + \frac{3}{32}K_1 + \frac{9}{32}K_2\right)$ 
10   $K_4 = h\vec{F}\left(t_n + \frac{12h}{13}, [X_n] + \frac{1932}{2197}K_1 - \frac{7200}{2197}K_2 + \frac{7296}{2197}K_3\right)$ 
11   $K_5 = h\vec{F}\left(t_n + h, [X_n] + \frac{439}{216}K_1 - 8K_2 + \frac{3680}{513}K_3 - \frac{845}{4104}K_4\right)$ 
12   $K_6 = h\vec{F}\left(t_n + \frac{h}{2}, [X_n] - \frac{8}{27}K_1 + 2K_2 - \frac{3544}{2565}K_3 + \frac{1859}{4104}K_4 - \frac{11}{40}K_5\right)$ 
13   $[X_{new}] = [X] + \frac{25}{216}K_1 + \frac{1408}{2565}K_3 + \frac{2187}{4104}K_4 - \frac{1}{6}K_5$ 
14   $[\tilde{X}_{new}] = [X] + \frac{16}{135}K_1 + \frac{6656}{12825}K_3 + \frac{28561}{56430}K_4 = \frac{9}{50}K_5 + \frac{2}{55}K_6$ 
15   $\Delta = \sqrt{\frac{[\tilde{X}_{new}] - [X_{new}]}{h}}$ 
16  if  $\Delta \leq \epsilon_t$  then
17     $[X] = [X_{new}]$ 
18     $t = t + h$ 
19   $\sigma = 0.84 \left(\frac{\epsilon_t}{\Delta}\right)^{\frac{1}{4}}$ 
20  if  $\sigma < 0.1$  then
21     $\sigma = 0.1$ 
22  if  $\sigma > 4$  then
23     $\sigma = 4$ 
24   $h = h\sigma$ 

```

---

### 5.6.2.2 Discussion

Even though the computation of the simulation step is more demanding than the RK4 method the possibility of changing  $h$  often decreases the simulation runtime.

### 5.6.3 Stiffness

An expected result of the adaptive method is that  $h$  is small in region where the solution curves display large variation and large in region when the solution have a near zero slope. This doesn't always happen: the stepsize  $h$  is forced to be small to an unacceptable level in region where solution curves are very small. This phenomenon is known as stiffness. A system of ODE is said to be stiff when a numerical solution of its initial value problem forces the numerical method to employ a discretization stepsize excessively small with respect to the smoothness of the exact solution. This

is a property of the couple of ODE system and numerical scheme used to solve. It could appear or disappear changing the numerical scheme. It doesn't arise only in adaptive methods, but it is important because the algorithm may lose control on the update of  $h$  with an impact on the runtime. In this cases the problem is solved by changing the numerical algorithm. Usually BDF methods are used to simulate a system of ODEs that exhibits stiffness with adaptive numerical simulation.

## 5.7 Issues of deterministic simulation

Regardless of the chosen numerical method the deterministic simulation provides only an approximation of the biochemical dynamics, this is often not a problem: the gain in simulation runtime compensates the loss in accuracy, especially for higher-order numerical methods. However there are some specific conditions in which deterministic simulation fails to compute the real behaviour of the system.

### 5.7.1 Spatial homogeneity and continuum hypothesis

In particular spatial homogeneity and the continuum hypothesis are not satisfied for biological processes involving low numbered chemical species because the dynamics could be partially or totally driven by few stochastic events impossible to observe by considering averaged dynamics. Even when the two hypothesis are satisfied some properties are impossible to observed.

### 5.7.2 Multistability

One of them is multistability: this is never observed by an averaged dynamics of the system because the deterministi simulation computes the same averaged dynamics when starting from the same initial state.

### 5.7.3 Steady state

Another condition that lead to important differences arises when the biochemical system is simulated from a steady state, a solution of the set of ODEs when all derivative are set to 0. This makes the averaged dynamics stationary. The asynchronous application of reaction firing in stochastic simulation could cause an exit from the equilibrium leading to non-stationary dynamics.

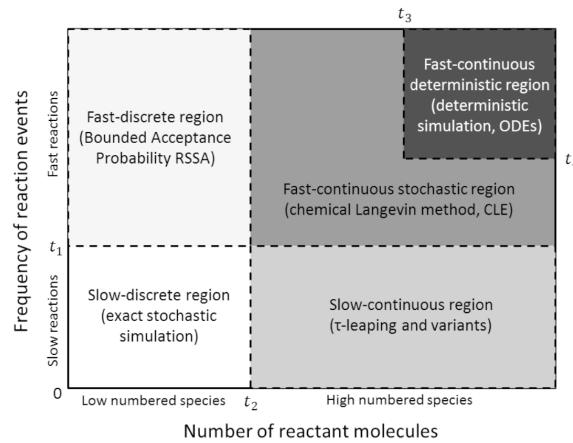
# Chapter 6

## Hybrid simulation approaches

### 6.1 Introduction

Hybrid simulation approaches refer to a class of methods that combines the advantages of complementary simulation approaches: the system is partitioned into subsystems that are simulated with different methods. When exact stochastic simulation is not a realistic option approximate strategies have to be considered together with their accuracy, so they often require the fulfilment of specific conditions. The state space associated with biochemical reaction networks can be partitioned into regions depending on the nature of the system, according to the number of molecules and the frequency of reaction events. This helps evaluate which approximations are reasonable. The essential elements are the abundance of the species and the frequency of reaction. Threshold variables demarcate the different partitions and they are model dependents as seen in figure 6.1:

- $t_1$  indicates whether a reaction is considered fast.
- $t_2$  indicates whether a population is abundant or not.
- $t_3$  and  $t_4$  the border between stochastic variation and deterministic behaviour.



**Figure 6.1:** Partitions of the state space

### 6.1.1 Slow-discrete region

The system is in a slow-discrete region when the reaction are slow and low numbered species are present. The species must be represented with an integer and discrete changes are allowed. Moreover the reaction events are rare and correspond to significant changes in the system. This region should be treated with the highest accuracy method available.

### 6.1.2 Fast-discrete region

The system is in the fast-discrete region whenever molecular populations are small and the reactions happen frequently enough that exact simulation could be intractable. This region can be treated with stochastic approximate algorithms developed to work with large reaction propensities and small populations like BA-RSSA.

### 6.1.3 Slow-continuous region

The system is in the slow-continuous region whenever molecular population are large and reaction are slow. The molecular populations can be assumed continuous and each reaction occurrence does not change significantly its species concentration. The simulation of many reaction occurrences can be skipped without affecting the accuracy. This region can be treated by the  $\tau$ -leaping algorithm.

### 6.1.4 Fast continuous stochastic and deterministic region

The system starts in the fast continuous stochastic and goes into the deterministic whenever it has fast reactions and high number species. In the first case the CLE can be considered for the simulation, while in the second deterministic simulations can be used.

### 6.1.5 Dimensionality explosion

The system is two dimensional only when it has one species and one reaction. When these two sets increase the criteria above can be applied only when all of them belong to the same region. This is a very strict condition that must be preserved along all of the simulation process. Hybrid simulation approaches try to solve this problem by dividing the system into parts that fit with the regions described which are then simulated by ad hoc simulation methods to provide the best compromise between accuracy and runtime.

## 6.2 Reaction-based system partitioning

The reaction based system partitioning partitions the system into subnetwork that reaquire to be simulated by the same strategy. The reaction are divided into  $\mathcal{R}^s$  and  $\mathcal{R}^f$  of slow and fast reactions. Fast reaction have high propensities and can be simulated by CLE or deterministic simulation while slow one have low propensities. When deterministic simulation is employed a preliminary step is required to transform the set of reactions in ODEs. Slow reactions require a more accurate stochastic simulation approache.

### 6.2.1 Classifying fast reactions

Reactions can be fast when it occurs many times in a small time interval and the effect of each reaction on the number of reactants and products is small, so quantitatively:

$$a_j \tau^f \geq \theta \ll 1$$

And:

$$\vec{x}_i > \lambda |\vec{v}_{ij}|, \forall S_i \in Reactants(R_j) \cup Products(R_j)$$

$\theta$  and  $\lambda$  define the minimum number of time a fast reaction can be applied within  $\tau^f$  and how fine grained the species must be in order for them to appear as continuous. Usually for practical models  $\theta = 10$  and  $\lambda = 100$ .

### 6.2.2 Partitioning algorithm

An implementation of this reaction-based partitioning can be found in algorithm 44

---

#### Algorithm 42: Two class reaction-based partitioning()

---

```

1 Input: a biochemical reaction system with stoichiometrix matrix  $\vec{v}$  and current state  $\vec{x}$ , the
   time increment  $\tau^f$  for the approximate simulation of fast reaction,  $\theta$  defining the minimum
   number of times that a fast reaction has to be applied on average within  $\tau^f$  and  $\lambda$ 
   indicating how fine grained the reactant and product species must be in order to be
   approximated by continuous numbers
2 Output: the sets  $\mathcal{R}^s$  and  $\mathcal{R}^f$ 
3  $\mathcal{R}^s = \emptyset$ 
4  $\mathcal{R}^f = \emptyset$ 
5 foreach  $R_j \in \mathcal{R}$  do
6   if  $a_j \tau^f < \tau$  then
7      $R_j \in \mathcal{R}^s$ 
8   else if  $\exists S_i \in Reactants(R_j) \cup Products(R_j) : \vec{x}_i \leq \lambda |\vec{v}_{ij}|$  then
9      $R_j \in \mathcal{R}^s$ 
10   else
11      $R_j \in \mathcal{R}^f$ 
```

---

### 6.2.3 Dynamic partitioning

Because reaction propensities and state vector change in time the partitioning has to be evaluated during the simulation. This is dynamic partitioning. It is important when the system state varies considerably over time. A fixed partitioning can be used when the subsystems are different and these differences remain constant during the simulation.

### 6.2.4 Different constraints

Some partitioning strategies depends only on the second condition and relax it to include only the reactants. This is to speed up the simulation by taking out the stochastically simulated fast reaction subsystem, while particle-number based partitioning is concerned with correctly treating reactions with small concentrations. Moreover  $\tau^f$  can change at each simulation step and can be not considered: the reaction are divided into a tentative partitioning and then a fixed point iterative scheme happens, tuning the partitioning so that the propensity of each fast reaction will be at least

## 6.2. REACTION-BASED SYSTEM PARTITIONING

---

$\lambda$  times larger than the fastest slow reaction. This procedure, outlined in algorithm 43 is more computationally demanding but has less parameters.

---

**Algorithm 43:** Two class reaction-based partitioning with fixed point iterations()

---

```

1 Input: a biochemical reaction system with stoichiometrix matrix  $\vec{v}$  and current state  $\vec{x}$ , the
   time increment  $\tau^f$  for the approximate simulation of fast reaction,  $\gamma$  indicating how fine
   grained the reactant and product species must be in order to be approximated by
   continuous numbers abd  $\lambda$  indicating how many times the propensity of the slowest fast
   reaction has to be larger than the propensity of the fastest slow reaction
2 Output: the sets  $\mathcal{R}^s$  and  $\mathcal{R}^f$ 
3  $a_{\max}^s = 0$ 
4  $\mathcal{R}^s = \emptyset$ 
5  $\mathcal{R}^f = \emptyset$ 
6 foreach  $R_j \in \mathcal{R}$  do
7   if  $\exists S_i \in \text{Reactants}(R_j) \cup \text{Products}(R_j) : \vec{x}_i \leq \gamma |\vec{v}_{ij}|$  then
8      $R_j \in \mathcal{R}^s$ 
9      $a_{\max}^s = \max\{a_{\max}^s, a_j\}$ 
10   else
11      $R_j \in \mathcal{R}^f$ 
12 if  $\mathcal{R}^s \neq \emptyset \wedge \mathcal{R}^f \neq \emptyset$  then
13 repeat
14    $\text{fxdpt} = \text{true}$ 
15 foreach  $R_j \in \mathcal{R}^f$  do
16   if  $a_j < \lambda a_{\max}^s$  then
17     move  $R_j$  from  $\mathcal{R}^f$  to  $\mathcal{R}^s$ 
18      $a_{\max}^s = \max\{a_{\max}^s, a_j\}$ 
19    $\text{fxdpt} = \text{false}$ 
20 until  $\text{fxdpt} = \text{true}$ 
```

---

### 6.2.5 Four class reaction partitioning

The reaction partitioning in two classes reduces at minimum the simulation strategies implemented in the hybrid algorithm, simplifying its implementation, but reducing the accuracy of the results. A higher number of reaction classes are introduced to be more consistent with the regions. A way of doing so is to divide it into fours set:

- Very slow reactions  $\mathcal{R}^{vs}$  requiring exact simulation.
- Medium reactions  $\mathcal{R}^m$ , requiring CLE.
- Slow reactions  $\mathcal{R}^s$  requiring a  $\tau$ -leaping method.
- Fast reactions  $\mathcal{R}^f$ , requiring deterministic simulation.

At the basis of this strategy is the computation of  $\tau$ , providing the next firing time of a model reaction and imposing the following restraints:

- $a_j \tau \leq 1$   $R_j$  very slow.

- $a_j\tau > 1 \wedge a_j\tau \not\gg 1$   $R_j$  is slow.
- $a_j\tau \gg 1 \wedge \sqrt{a_j\tau} \not\gg 1$   $R_j$  is medium.
- $\sqrt{a_j\tau} \gg 1$   $R_j$  is fast.

#### 6.2.5.1 Algorithm

An implementation of the four class reaction based partitioning is outlined in algorithm ??, introducing  $\theta$  to implement the  $\gg$  constraint

---

**Algorithm 44:** Two class reaction-based partitioning()

```

1 Input: a biochemical reaction system with current state  $\vec{x}$ , the firing time  $\tau$  of the next
   model reaction and the threshold parameter  $\theta$ 
2 Output: the sets  $\mathcal{R}^{vs}$ ,  $\mathcal{R}^s$ ,  $\mathcal{R}^m$  and  $\mathcal{R}^f$ 
3  $\mathcal{R}^{vs} = \emptyset$ 
4  $\mathcal{R}^f = \emptyset$ 
5  $\mathcal{R}^m = \emptyset$ 
6  $\mathcal{R}^s = \emptyset$ 
7 foreach  $R_j \in \mathcal{R}$  do
8   if  $a_j\tau \leq 1$  then
9      $R_j \in \mathcal{R}^{vs}$ 
10  else if  $a_j\tau < \theta$  then
11     $R_j \in \mathcal{R}^s$ 
12  else if  $\sqrt{a_j\tau} < \theta$  then
13     $R_j \in \mathcal{R}^m$ 
14  else
15     $R_j \in \mathcal{R}^f$ 

```

---

## 6.3 Synchronization of exact and approximate simulations

When the hybrid strategy moves forward one simulation step, slow reaction are simulated by exact stochastic simulation while less accurate strategies are used for faster reactions. The approximate simulation of faster reactions is constrained to not exceed the firing time of the first slow reaction. This is a synchronization to preserve the accuracy of the simulation. Even if the simulation of slow reactions is exact, their firing is not guaranteed to be exact when faster reactions are simulated in an approximate way. Since the approximation is difficult to obtain many hybrid algorithm implement a simulation for slow reactions that is not exact, but less approximate than the one of the fast reactions.

#### 6.3.1 Algorithm

An implementation of a four class hybrid simulation strategy is implemented in algorithm 45.

---

**Algorithm 45:** Four class hybrid simulation strategy()

---

```

1 Input: a biochemical reaction system with initial state  $X_0$ , the simulation ending time
    $T_{\max}$  and the threshold parameter  $\theta > 1$ 
2 Output: a trajectory of the biochemical system
3  $t = 0$ 
4  $X = X_0$ 
5 while  $t < T_{\max}$  do
6   compute  $\tau$  according to the  $\tau$ -leaping method
7   repeat
8      $updateNeeded = \text{false}$ 
9     foreach  $R_j \in \mathcal{R}$  do
10        $\mathcal{R}^{vs}, \mathcal{R}^s, \mathcal{R}^m, \mathcal{R}^f = \text{partitioning}(\mathcal{R}, \theta, \tau)$ 
11       foreach  $R_j \in \mathcal{R}^{vs}$  do
12         compute  $\tau_f$  using exact simulation algorithm
13         if  $\mathcal{R}^{vs} = \mathcal{R} \wedge \tau \neq \min\{\tau_j\}, R_j \in \mathcal{R}^{vs}$  then
14            $\tau = \min\{\tau_j\}, R_j \in \mathcal{R}^{vs}$ 
15         if  $\tau > \min\{\tau_j\}, R_j \in \mathcal{R}^{vs}$  then
16            $\tau = \min\{\tau_j\}, R_j \in \mathcal{R}^{vs}$ 
17            $updateNeeded = \text{true}$ 
18         if  $\neg updateNeeded$  then
19           compute  $X^{new}$  at  $t + \tau$  approximating the firing of reactions in  $\mathcal{R}^s, \mathcal{R}^m, \mathcal{R}^f$ 
             accorrding to:
20            $\tau$ -leaping method for slow reactions
21           CLE for medium reactions
22           deterministic simulation for fast reactions
23           update  $X^{new}$  by applying  $R_j \in \mathcal{R}^{vs}$ , such that  $\tau_j = \tau$ 
24           if any  $X_i^{new} < 0$  then
25              $\tau = \frac{\tau}{2}$ 
26              $updateNeeded = \text{true}$ 
27           else
28              $X = X^{new}$ 
29              $t = t + \tau$ 
30   until  $\neg updateNeeded$ 

```

---

### 6.3.2 Preserving the exactness

In order to preserve the exactness of the simulation of slow reactions, the reaction probability density has to be extended to consider time-varying transition propensities account for the propensities of slow reactions that change due to the simulation of fast reactions. The pdf of the next firing of a slow reaction  $R_\mu \in \mathcal{R}^s$  becomes:

$$p^s(\tau, \mu | \vec{x}, t) = a_\mu(X(t + \tau)) e^{- \int_t^{t+\tau} a_0^s(X(t')) dt'}$$

Where  $X(t + \tau)$  is the system at time  $t + \tau$ ,  $\vec{x}$  is the current system state and:

$$a_0^s = \sum_{R_j \in \mathcal{R}^s} a_j$$

The firing time of the next slow reaction is obtained by solving:

$$\int_t^{t+\tau} a_0^s(X(t')) dt' = -\ln(r)$$

This solution is difficult to compute: the system state is changed by fast reactions during the time interval. The hybrid simulation has to evaluate it simultaneously with the simulation of the fast reaction to generate the next slow reaction event.

### 6.3.2.1 Event detection

In order to satisfy the time integral the simulation of fast reaction has to include an event detection part. The easiest way to do so is to relax the constraint of the equation to find a time instant along the simulation such that:

$$\left| \int_t^{t+\tau} a_0^x(X(t')) dt' + \ln(r) \right| \leq \epsilon$$

Where  $\epsilon \approx 0$  is a positive error threshold. This makes the simulation of slow reaction depend on  $\epsilon$ . This correspond to adding to the set of deterministic ODEs an additional equation:

$$\frac{dRES}{dt} = a_0^x RES(0) = \ln(r)$$

This is numerically integrated together with the set of ODE until  $|RES(t + \tau)| \leq \epsilon$ . The computation of the firing time of the next slow reaction will be not exact because it depends on the order of the numerical method used to solve the initial value problem.

### 6.3.2.2 Algorithm

A two class hybrid strategy with exact simulation of slow reactions is outlined in algorithm 46

---

**Algorithm 46:** Two class hybrid strategy with exact simulation of slow reactions()

---

**1 Input:** a biochemical reaction system with initial state  $X_0$ , the simulation ending time  $T_{\max}$   
**2 Output:** a trajectory of the biochemical system  
**3**  $t = 0$   
**4**  $X = X_0$   
**5 while**  $t < T_{\max}$  **do**  
**6   foreach**  $R_j \in \mathcal{R}$  **do**  
**7** $\mathcal{R}^s, \mathcal{R}^f = \text{partitioning}(\mathcal{R})$   
**8**generate two uniform random numbers  $r_1, r_2 \sim \text{norm}(0, 1)$   
**9**compute  $X_{\text{new}}$  from  $X$  by approximating the firing of fast reactions until  $t + \tau$  is reached  
**10**that satisfied the integral  $\int_t^{t+\tau} a_0^s(X(t')) dt' + \ln(r) = 0$   
**11**select the slow reaction  $R_\mu \in \mathcal{R}^s$  with the smallest  $\mu$  such that  $\sum_{j=1}^{\mu} a_j > r_2 a_0^s$   
**12**update  $X_{\text{new}}$  by applyinh  $R_\mu$   
**13** $t = t + \tau$

---

## 6.4 Hybrid Rejection-Based SSA

The hybrid rejection based stochastic simulation algorithm HRSSA is built on top of RSSA. The simulation strategy relies on the concept of fluctuation interval:

$$[\underline{\vec{x}}, \bar{\vec{x}}] = [(1 - \delta)\vec{x}, (1 + \delta)\vec{x}], 0 < \delta < 1$$

Used to obtain exact stochastic simulation of slow reactions without computing the integral, improving simulation accuracy and runtime.

### 6.4.1 Reaction partitioning

Reactions are partitioned in two classes and the partition is updated only when the current system does not fit any more in its fluctuation interval: the partitioning is done considering the lower bound  $\underline{\vec{x}}$ . This does not affect the accuracy of the classification, but it imposes more stringent constraints that increase the number of reactions classified as slow.

### 6.4.2 Firing time

The sum of the upper propensity bounds of slow reactions is computed:

$$\bar{a}_0^s = \sum_{R_j \in \mathcal{R}^s} \bar{a}_j = \sum_{R_j \in \mathcal{R}^s} a_j(\bar{\vec{x}})$$

The firing time of a candidate slow reaction is:

$$\tau = -\frac{\ln r}{\bar{a}_0^s}$$

Where  $r \sim \text{norm}(0, 1)$ . If the system state remains in the fluctuation interval  $\bar{a}_0^s$  is not dependent on time in  $[t, t + \tau]$ , allowing to simulate fast reactions over this interval without an side effect on slow reactions.

### 6.4.3 Updating the system

After the simulation of fast reaction in  $[t, t + \tau]$ , a slow reaction is chosen and validated to fire. To preserve the exactness, the feasibility of the current system must be preserved during the simulation of the fast reactions. Every time the system state exists from its bounds the simulation has to be stopped and the fluctuation interval is updated. Fast reactions are simulated in  $[r, t + \tau']$ , where  $t + \tau'$  is the last computed time step  $\tau' \leq \tau$  that does not violate the feasibility of the current system state. When  $\tau' < \tau$ , the simulation process is stopped and the fluctuation interval of the system state is updated, ensuring correct synchronization. When  $\tau' = \tau$ , the state can be updated by applying one slow reaction  $R_j$ , selected according to the RSSA simulation strategy.

### 6.4.4 Algorithm

An implementation of HRSSA is outlined in algorithm 47.

#### 6.4. HYBRID REJECTION-BASED SSA

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**Algorithm 47:** Hybrid Rejection-Based SSA (HRSSA)()

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**1 Input:** a biochemical reaction system with initial state  $X_0$ ,  $\delta$  to compute the fluctuation interval,  $\tau^f$ ,  $\theta$ ,  $\gamma$  to partition the system and simulation ending time  $T_{\max}$ .

**2 Output:** a trajectory of the biochemical reaction system

3  $t = 0$

4  $\vec{X} = \vec{x}_0$

5 **while**  $t < T_{\max}$  **do**

6    $[\underline{X}, \bar{X}] = [(1 - \delta)X, (1 + \delta)X]$

7   **foreach**  $R_j \in \mathcal{R}$  **do**

8     compute  $\bar{a}_j$  and  $a_j$

9      $\mathcal{R}^s, \mathcal{R}^f = \text{partition}(\underline{X}, \gamma, \theta, \tau^f)$

10    bound the system state  $\underline{X}$  according to  $\gamma, \theta, \tau^f$

11    $\bar{a}_0^s = \sum_{R_j \in \mathcal{R}^s} \bar{a}_j$

12   updateNeeded = **false**

13   **while**  $t < T_{\max} \wedge \neg \text{updateNeeded}$  **do**

14      $r \sim \text{norm}(0, 1)$

15      $\tau = -\frac{\ln r}{\bar{a}_0^s}$

16     compute  $X(t + \tau')$  by simulating  $\mathcal{R}^f$  at time steps of maximum length  $\tau^f$ , where  $t + \tau'$  is the last computed step such that  $\tau' \leq \tau \wedge X(t + \tau') \in [\underline{X}, \bar{X}]$

17     **if**  $\tau' = \tau$  **then**

18       generate  $r_1, r_2 \sim \text{norm}(0, 1)$

19       accepted = **false**

20       select  $R_\mu \in \mathcal{R}^s$  with smallest  $\mu$  such that  $\sum_{j=1}^{\mu} \bar{a}_j > r_i \bar{a}_0^s$

21       **if**  $r_2 \leq \frac{a_\mu}{\bar{a}_\mu}$  **then**

22         accepted = **true**

23       **else**

24         compute  $a_\mu(X(t + \tau'))$

25         **if**  $r_2 \leq \frac{a_\mu(X(t + \tau'))}{\bar{a}_\mu}$  **then**

26           accepted = **true**

27       **if** accepted = **true** **then**

28         update  $X(t + \tau')$  by applying  $R_\mu$

29         **if**  $X(t + \tau') \notin [\underline{X}, \bar{X}]$  **then**

30           updateNeeded = **true**

31       **else**

32         updateNeeded = **true**

33        $X = X(t + \tau')$

34        $t = t + \tau'$

---

#### 6.4.5 Correctness of the simulation of slow reactions

HRSSA simulates slow reactions exactly under the hypothesis that the system state remains in its fluctuation interval during the simulation. Let  $p_1^s(\tau|\vec{x}, t)$  be the pdf of the firing time  $\tau$  such that  $p_1^s(\tau|\vec{x}, t)d\tau$  gives the probability that the slow reaction is selected to fire at time  $t + \tau$ . Let  $p_2^s(\mu|\tau, \vec{x}, t)$  be the probability that the slow reaction is  $R_\mu$  assuming that  $\vec{x} \in [\underline{X}, \bar{X}]$ . The multiplication of  $p_1^s$  and  $p_2^s$  gives the joint probability density function of the next slow reaction  $R_\mu$  firing at  $t + \tau$ , sampled by HRSSA. To compute  $p_1^s(\tau|\vec{x})$  let  $\mathbb{P}\{R^s\}$  be the probability that some slow reaction is accepted by HRSSA at  $t + \tau$ :

$$\mathbb{P}\{R^s\} = \frac{\int_t^{t+\tau} \sum_{R_j \in \mathcal{R}^s} a_j(X(t')) dt'}{\bar{a}_0^s} = \frac{\int_t^{t+\tau} a_0^s(X(t')) dt'}{\bar{a}_0^s \tau}$$

If  $k$  is the number of attempts before a reaction is accepted,  $k$  is geometrically distributed with success probability  $\mathbb{P}\{R^s\}$ . For a fixed  $k$ ,  $\tau$  is an Erlang distribution of parameters  $k$  and  $a_0^s(\vec{x})$ . Summing over all possible  $k$ :

$$p_1^s(\tau|\vec{x}, t) = \sum_{k=1}^{\infty} f_{erlang}(k, \bar{a}_0^s)(\tau) \mathbb{P}\{R^s\} (1 - \mathbb{P}\{R^s\})^{k-1}$$

Where  $f_{erlang}(k, \bar{a}_0^s)$  is the pdf of the Erlang distribution. Substituting the formula of  $\mathbb{P}\{R^s\}$  and recalling:

$$f_{erlang}(k, \bar{a}_0^s) = \frac{(\bar{a}_0^s)^k \tau^{k-1} e^{-\bar{a}_0^s \tau}}{(k-1)!}$$

Then:

$$\begin{aligned} p_1^s(\tau|\vec{x}, t) &= \sum_{k=1}^{\infty} \frac{(\bar{a}_0^s)^k \tau^{k-1} e^{-\bar{a}_0^s \tau}}{(k-1)!} \frac{\int_t^{t+\tau} a_0^s(X(t')) dt'}{\bar{a}_0^s \tau} \left(1 - \frac{\int_t^{t+\tau} a_0^s(X(t')) dt'}{\bar{a}_0^s \tau}\right)^{k-1} = \\ &= \frac{\int_t^{t+\tau} a_0^s(X(t')) dt'}{\tau} e^{-\bar{a}_0^s \tau} \sum_{k=1}^{\infty} \frac{(\bar{a}_0^s \tau - \int_t^{t+\tau} a_0^s(X(t')) dt')^{k-1}}{(k-1)!} = \\ &= \frac{\int_t^{t+\tau} a_0^s(X(t')) dt'}{\tau} e^{-\bar{a}_0^s \tau} e^{\bar{a}_0^s \tau - \int_t^{t+\tau} a_0^s(X(t')) dt'} = \\ &= \frac{\int_t^{t+\tau} a_0^s(X(t')) dt'}{\tau} e^{-\int_t^{t+\tau} a_0^s(X(t')) dt'} \end{aligned}$$

Now let  $\mathbb{P}\{R_\mu\}$  be the probability that  $R_\mu$  is selected and accepted at  $t + \tau$  given that some reaction is accepted at that time  $\mathbb{P}\{R_\mu\}$  is the multiplication of the probability that  $R_\mu$  is selected and is accepted:

$$\mathbb{P}\{R_\mu\} = \frac{\bar{a}_\mu}{\bar{a}_0^s} \frac{a_\mu(X(t + \tau))}{\bar{a}_\mu} = \frac{a_\mu(X(t + \tau))}{\bar{a}_0^s}$$

Which combining with  $\mathbb{P}\{R^s\}$ :

$$p_2^s(j|\tau, \vec{x}, t) = \frac{\mathbb{P}\{R_\mu\}}{\mathbb{P}\{R\}} = \frac{\frac{a_\mu(X(t + \tau))}{\bar{a}_0^s}}{\frac{\int_t^{t+\tau} a_0^s(X(t')) dt'}{\bar{a}_0^s \tau}} = \frac{a_\mu(X(t + \tau)) \tau}{\int_t^{t+\tau} a_0^s(X(t')) dt'}$$

Now:

$$p_1^s(\tau|\vec{x}, t)p_2^s(j|\tau, \vec{x}, t) = a_\mu(X(t+\tau))e^{-\int_t^{t+\tau} a_0^s(X(t'))dt'}$$

Which is equal to  $p^s(\tau, \mu|\vec{x}, t)$  proving the correctness of HRSSA.

## 6.5 Hybrid simulation with stiffness

Fast reactions have highly reactive species which may have a low population which quickly equilibrates to a stochastic equilibrium distribution on the time scales of slow reactions. This is kept changing over time due to the firings of reactions, but its distribution remains. This equilibrium could be altered by slow reactions. This behaviour is called stiffness and it often arises from the quasi-steady state (QSS) or the reaction partial equilibrium (PE). The former concentrates on the state, while the latter on the reactions. QSS assumes that the changes in populations of fast species is fast with respect to slow species, while PE assumes that fast reactions involving only fast species quickly equilibrate to a stationary distribution in the time scale of slow reactions. Under stiffness the behaviour of species at equilibrium is averaging and the dynamics are formulated conditionally on the limiting of these species, skipping the detailed simulation of the fast reactions.

### 6.5.1 Formulation of reactions with stiffness

Consider a biochemical network where species are partitioned into a fast  $\mathcal{S}^f$  and slow  $\mathcal{S}^s$ . If a species is highly active is a fast or intermedie species in  $\mathcal{S}^f$ , otherwise it is a slow or primary species. The state vector is  $X = (X^f, X^s)$  and the state change vector of  $R_j$  is  $\vec{v}_j = (\vec{v}_j^f, \vec{v}_j^s)$ . Let now  $X(t) = (X^f(t), X^s(t)) = (\vec{x}^f, \vec{x}^s)$  the state at  $t$ . The CME equation can be written as:

$$\frac{d\mathbb{P}\{\vec{x}^f, \vec{x}^s, t\}}{dt} = \sum_{j=1}^M (a_j(\vec{x}^f - \vec{v}_j^f, \vec{x}^s - \vec{v}_j^s)\mathbb{P}\{\vec{x}^f - \vec{v}_j^f, \vec{x}^s - \vec{v}_j^s, t\}) - \mathbb{P}\{\vec{x}^f, \vec{x}^s, t\} \sum_{j=1}^M a_j(\vec{x}^f, \vec{x}^s)$$

The initial state in the condition has been omitted to simplify the notation. The probability can be factorized as:

$$\mathbb{P}\{\vec{x}^f, \vec{x}^s, t\} = \mathbb{P}\{\vec{x}^s, t\}\mathbb{P}\{\vec{x}^f | \vec{x}^s, t\}$$

Differentiating both sides with respect to time:

$$\frac{d\mathbb{P}\{\vec{x}^f, \vec{x}^s, t\}}{dt} = \mathbb{P}\{\vec{x}^f | \vec{x}^s, t\} \frac{d\mathbb{P}\{\vec{x}^s, t\}}{dt} + \mathbb{P}\{\vec{x}^s, t\} \frac{d\mathbb{P}\{\vec{x}^f | \vec{x}^s, t\}}{dt}$$

Resulting in:

$$\begin{aligned} \mathbb{P}\{\vec{x}^f | \vec{x}^s, t\} \frac{d\mathbb{P}\{\vec{x}^s, t\}}{dt} + \mathbb{P}\{\vec{x}^s, t\} \frac{d\mathbb{P}\{\vec{x}^f | \vec{x}^s, t\}}{dt} &= \\ &= \sum_{j=1}^M (a_j(\vec{x}^f - \vec{v}_j^f, \vec{x}^s - \vec{v}_j^s)\mathbb{P}\{\vec{x}^f - \vec{v}_j^f, \vec{x}^s - \vec{v}_j^s, t\}\mathbb{P}\{\vec{x}^s - \vec{v}_j^s, t\}) + \\ &\quad \mathbb{P}\{\vec{x}^f | \vec{x}^s, t\}\mathbb{P}\{\vec{x}^s, t\} \sum_{j=1}^M a_j(\vec{x}^f, \vec{x}^s) \end{aligned}$$

## 6.5. HYBRID SIMULATION WITH STIFFNESS

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Now summing both sides over all possible value of  $\vec{x}^f$  and noting that:

- $\sum_{\vec{x}^f} \mathbb{P}\{\vec{x}^f | \vec{x}^s\} = 1$
  - $\sum_{\vec{x}^f} \frac{d\mathbb{P}\{\vec{x}^f | \vec{x}^s\}}{dt} = \frac{d \sum_{\vec{x}^f} \mathbb{P}\{\vec{x}^f | \vec{x}^s\}}{dt} = 0$
- $$\frac{d\mathbb{P}\{\vec{x}^s, t\}}{dt} = \sum_{j=1}^M \hat{a}_j(\vec{x}^s - \vec{v}_j^s) \mathbb{P}\{\vec{x}^s - \vec{v}_j^s, t\} - \mathbb{P}\{\vec{x}^s, t\} \sum_{j=1}^M \hat{a}_j(\vec{x}^s)$$

Where:

$$\hat{a}_j(\vec{x}_s) = \sum_{\vec{x}^f} a_j(\vec{x}^f, \vec{x}^s) \mathbb{P}\{\vec{x}^f | \vec{x}^s, t\}$$

Is the slow scale propensity: it is the average propensity of a reaction over a fast species. This is the conditional mean of propensity  $a_j(\vec{x}^f, \vec{x}^s)$  with respect to  $\mathbb{P}\{\vec{x}^f | \vec{x}^s, t\}$ . This equation defines a CME for a slow species, To simulate it the QSS assumption or the PE assumption have to be considered: the slow scale propensity is affected by the time-dependent probability  $\mathbb{P}\{\vec{x}^f | \vec{x}^s, t\}$ . In QSSA the net change in the population of fast species is assumed to be approximately zero. PEA assumes that the fast reactions that reach equilibrium remain in it. These allow to approximate the slow-scale propensity and a stochastic simulation algorithm can then be adapted to simulate the dynamics of slow species.

### 6.5.1.1 Quasi-steady state assumption

Under QSSA the slow scale propensity is approximated by replacing the probability by a time-invariant one:

$$\hat{a}_j(\vec{x}^s) \approx \sum_{\vec{x}^f} a_j(\vec{x}^f, \vec{x}^s) \mathbb{P}\{\vec{x}^f | \vec{x}^s\}$$

This is obtained by imposing:

- The dynamics of the state  $X^f$  conditional on  $X^s$  is Markovian:  $\mathbb{P}\{\vec{x}^f | \text{vec}x^s, t\}$  satisfies the CME equation.
- The net change  $\mathbb{P}\{\vec{x}^f | \vec{x}^s, t\}$  is approximately zero:  $\frac{d\mathbb{P}\{\vec{x}^f | \vec{x}^s, t\}}{dt} = 0$ .

Let  $\mathcal{R}^f$  the set of fast reactions that drive  $\mathcal{S}^f$  into an equilibrium. Note that the fast reactions can involve a slow species state. The time-invariant probability distribution is the solution of:

$$\sum_{R_j \in \mathcal{R}^f} (a_j(\vec{x}^f - \vec{v}_j^f, \vec{x}^s) \mathbb{P}\{\vec{x}^f - \vec{v}_j^f | \vec{x}^s\}) - \mathbb{P}\{\vec{x}^f, \vec{x}^s\} \sum_{j=1}^M a_j(\vec{x}^f, \vec{x}^s) = 0$$

### 6.5.1.2 Partial equilibrium assumption

The partial equilibrium assumption PEA is an alternative to approximate slow-scale propensity. It is done by uncoupling the dynamics of  $X^f$  from  $X^s$  in the computation of its stationary distribution. The equilibrium distribution  $\mathbb{P}\{\vec{x}^f|\vec{x}^s, t\} \approx \mathbb{P}\{\vec{x}^f(\infty)\}$ . The slow scale propensity then is computed as:

$$\hat{a}_j(\vec{x}^s) \approx \sum_{\vec{x}^f} a_j(\vec{x}^f, \vec{x}^s) \mathbb{P}\{\vec{x}^f(\infty)\}$$

Reactions are first provisionally partitioned into  $\mathcal{R}^f$  and  $\mathcal{R}^s$ . A reaction is put into  $\mathcal{R}^f$  if its propensity is much larger than a reaction in  $\mathcal{R}^s$ . Species of reactions in  $\mathcal{R}^f$  are put into  $\mathcal{S}^f$  with state  $X^f$ , while for slow one they are put into  $\mathcal{S}^s$  with state  $X^s$ . Fast species can participate as a reactant in a slow reaction while slow species cannot participate in a reactant in a fast one. The behaviour of fast species can be affected by slow ones. To uncouple slow species from the fast one, fast reactions are assumed to quickly reach an equilibrium distribution. The dynamics of  $X^f$  can uncouple from  $X^s$  by defining a virtual fast process  $\hat{X}^f$  composed of  $X^f$  evolved through fast reactions only. This virtual fast process is only dependent on fast reactions and its probability distribution satisfies a CME, and its probability reaches a stationary distribution quickly:

$$\lim_{t \rightarrow \infty} \mathbb{P}\{\vec{x}^f, t\} = \mathbb{P}\{\vec{x}^f(\infty)\}$$

The stationary distribution of fast species is the solution of:

$$\sum_{R_j \in \mathcal{R}^f} (a_j(\vec{x}^f - \vec{v}_j^f, \vec{x}^s) \mathbb{P}\{\vec{x}^f - \vec{v}_j^f\}) - \mathbb{P}\{\vec{x}^f\} \sum_{j=1}^M a_j(\vec{x}^f, \vec{x}^s) = 0$$

### 6.5.2 Slow-scale stochastic simulation algorithm

The slow scale stochastic simulation algorithm ssSSA simulates the dynamical behaviour of slow species. The species have to be partitioned into slow and fast and the fast equilibrate to a stationary distribution under QSSA or PE. It supposes to be able to generate value for fast species state  $X^f$  and to compute  $\hat{a}_j$  assuming that there exists an explicit formula for  $\mathbb{P}\{\vec{x}^f|\vec{x}^s\}$  or  $\mathbb{R}\{\vec{x}^f(\infty)\}$ . For each slow reaction where the sum over all possible values of  $X^f$  given its stationary distribution is:

$$\hat{a}_j(\vec{x}^s) \approx a_j * \langle X^f \rangle, \vec{x}^s$$

This approximation is exact if the propensity is linear with respect to fast species.

#### 6.5.2.1 Algorithm

An implementation of ssSSA is outlined in algorithm 48.

**Algorithm 48: Slow-scale SSA (ssSSA)()**


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```

1 Input: a biochemical reaction network of  $M$  reactions and  $N$  species. Partition the state
   into  $X^f$  and  $X^s$ . Find the stationary distribution for  $X^f$  as the method for generating a
   random value for the corresponding distribution
2 Output: a trajectory of the biochemical reaction network
3  $t = 0$ 
4  $\vec{X} = \vec{x}_0$ 
5 while  $t < T_{\max}$  do
6   compute  $\langle X_f \rangle$  from its stationary probability distribution
7    $\hat{a}_j(\vec{x}^s) \approx a_j * \langle X^f \rangle, \vec{x}^s$ 
8    $\hat{a}_i = \sum_{j=0}^M \hat{a}_j$ 
9    $r_1, r_2 \sim \text{norm}(0, 1)$ 
10  select  $R_\mu$  with minimum  $\mu$  such that  $\sum_{j=1}^\mu \hat{a}_j \geq r_1 \hat{a}_0$ 
11   $\tau = \frac{1}{\hat{a}_0} \ln \frac{1}{r_2}$ 
12   $X = X + \vec{v}_\mu$ 
13   $t = t + \tau$ 

```

---

### 6.5.3 Nested stochastic simulation algorithm

Finding an explicit analytical expression is often difficult, so is a direct computation of  $\hat{a}_j$ . The nested stochastic algorithm nSSA is an alternative approach that approximates  $\hat{a}_j$  on the fly. Two nested SSA simulations are used in which the inner loop simulates the fast reaction and approximates  $\hat{a}_j$ , while the other simulates the slow subset. Let  $X(t) = (\vec{x}^f, \vec{x}^s)$ , be the state at  $t$ . The simulation is two consecutive SSAs. The first computes  $\hat{a}_j$  for a slow reaction while it simulates the fast reactions as:

$$\hat{a}_j(\vec{x}^s) \approx \frac{1}{K} \sum_{i=1}^K \frac{1}{\Delta_{ft}} \int_t^{t+\Delta_{ft}} a_j(\vec{x}^f, \vec{x}^s) dt$$

Here  $K$  and  $\Delta_{ft}$  are predefined number of simulations and time interval for the fast reactions on which the error depends. When they reach  $\infty$  the computation converges to an exact value. The time interval can be chosen small because the fast reactions under stiffness quickly approach the equilibrium. Then the second step is used to select the next slow reaction in the slow reaction subset.

#### 6.5.3.1 Algorithm

An implementation of nSSA is outlined in algorithm 49.

**Algorithm 49: Nested SSA (nSSA)()**

**1 Input:** a biochemical reaction network of  $M$  reactions and  $N$  species. Partition the state into  $X^f$  and  $X^s$ , the simulation ending time  $T_{\max}$ , the time discretization  $\Delta_f t$  and the number of simulation runs  $K$  for simulating fast reactions.

**2 Output:** a trajectory of the biochemical reaction network

**3**  $t = 0$

**4**  $\vec{X} = \vec{x}_0$

**5 while**  $t < T_{\max}$  **do**

**6**    simulate only the fast reaction subset by  $K$  runs of SSA from  $t$  to  $t + \Delta_f t$

**7**     $\hat{a}_j(\vec{x}^s) \approx \frac{1}{K} \sum_{i=1}^K \frac{1}{\Delta_f t} \int_t^{t+\Delta_f t} a_j(\vec{x}^f, \vec{x}^s) dt$

**8**     $\hat{a}_0 = \sum_{R_j \in \mathcal{R}^f} \hat{a}_j$

**9**     $r_1, r_2 \sim \text{norm}(0, 1)$

**10**    select  $R_\mu$  with minimum  $\mu$  such that  $\sum_{j=1}^\mu \hat{a}_j \geq r_1 \hat{a}_0$

**11**     $\tau = \frac{1}{\hat{a}_0} \ln \frac{1}{r_2}$

**12**     $X = X + \vec{v}_\mu$

**13**     $t = t + \tau$

## Part II

# Parameter optimization

# Chapter 7

## Reali

### 7.1 Introduction

The course follows the structure of the article *Optimization Algorithms for Computational Systems Biology*.

#### 7.1.1 Definition of a system

A system is a set of integrated and interacting *components* or *entities* that form a whole with definite boundaries and surrounding environment. A system has a goal to achieve by performing one or more functions or tasks. Systems can be aggregated into a *hierarchy*. A system at a given level of detail can be a component at a higher level of detail.

- A *complex* (non-linear) *system* is a system that does not satisfy the principle of superposition, i.e., the behavior of the system cannot be inferred from the behavior of its components.
- A *dynamical system* is a system where fixed rules define the time dependencies of the system in a geometrical space. Dynamical systems have a space and time dimension because they change their characteristics over time. If we pick snapshots of the system at different time points, we observe different configurations of the system (data).

A *configuration* or state of the system refers to the current condition of the system and stores enough information to predict its next move. A state is characterized by the position of its components in a geometrical space and by the values of the attributes of its components (e.g., concentration or number of each elements involved). Systems change their state over time by changing the location of some of their components or changing the attributes of some of their components.

- *steady state*: some of the attributes of the system are no longer changing in the future.
- *transient state*: time needed to reach the steady state.

#### 7.1.2 Determinism, nondeterminism, or stochasticity?

- *Deterministic systems* always react in the same way to the same set of stimuli. These systems are completely determined by the initial state and the input set. The essence of deterministic systems is that each event is causally related to previous events and choices are always resolved in the same way in the same context. When a system generates multiple

## 7.1. INTRODUCTION

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outcomes from the same input in different observations, the system is **nondeterministic** (we cannot predict the output from the input).

- **Stochasticity** is the quality of lacking any predictable order or plan and stochastic systems possess some inherent randomness. It is possible to transform a nondeterministic system into a stochastic one by attaching probabilities to the selection points so that we turn nondeterministic choices into probabilistic choices.

### 7.1.3 Computational complexity

Complexity arises when interacting components self-organize to form evolving structures that exhibit a hierarchy of emergent system properties. An **emergent behavior** can be originated by a collection of components that interact in the absence of a centralized point of control to produce something that has not been designed or programmed in the system construction or evolution. Example: internet, ant colonies, consciousness.

**Computational complexity** is the amount of resources, measured as a function of the size of the input, needed to execute an algorithm.

- Computational space complexity: the amount of memory needed;
- Computational time complexity: the number of instructions to be executed.

### 7.1.4 Definition of a model

A *representation* is a set of symbols used to convey information and knowledge about a system. It is either physical as a cell or an ecosystem, or artificial as a computer network or an economic market. An abstraction is a representation that ignores some aspects of a system which are not of interest for the current investigation.

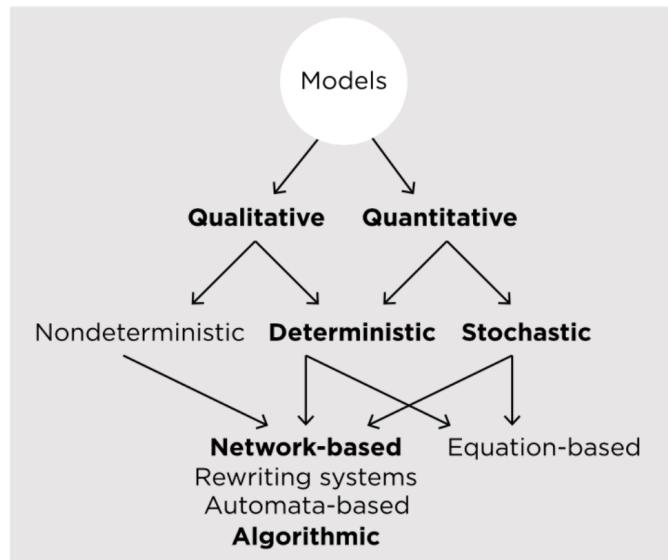
A *model* is an abstraction of a system. A model has its own interacting components that are characterized by the attributes that we want to observe. The set of all the attributes in a model is the *experimental frame*.

- A *dynamic model* aims at predicting the behavior of the system in time/space through what if analysis. **What if analysis** investigates how a change in some attributes affects the behavior of the modeled system.
- A *computational model* is a model that can be manipulated by a computer to observe properties of the corresponding system.

### 7.1.5 Checking the validity of a model

*Validity* is a fundamental property of models and witnesses the capacity of a model of making good predictions. We need to assess the validity of a model before using it to predict the behavior of a system.

Assume that  $M$  is a model for the system  $S$  and  $\underline{M}$  is the modeling process. Let  $s(t)$  and  $m(t)$  be the state of the system and of the model at time  $t$ , and  $f_s$  and  $f_m$  the state transition functions of the system and of the model, respectively. Finally, let  $I_s(t)$  and  $O_s(t)$  be the input and output of the system at time  $t$ . Similarly, we write  $I_m(t)$  and  $O_m(t)$  for the model.



**Figure 7.1:** From a model to methods

What we expect is that going from one state to the other we have a function (one for the system and one for the model); in a mathematical model we integrate the  $f_m$  function to known what happens in the transition of the model, but we cannot do that in the real setting (the transition function  $f_s$  is not known) → when dealing with nature, we cannot validate models according to the previous definition, so we use I/O validity, based on known input and outputs of the system.

The input and output are here generalized concepts: input can be any perturbation of the system or of the model, and output can be any observable property causally related to the input.

A model  $M$  is valid for a system  $S$  if:  $f_m(M(s(t_0))) = M(f_s(s(t_0))) = m(t_1)$   
 I/O validity can be checked by using data sets produced by the model and observed and measured on the system. An issue in this comparison process is *overfitting*:

- a model is well tuned to a specific dataset used to build the model
- it performs poorly on other datasets

**Cross-validation:** check overfitting by testing the model on data sets different from the ones used to build and calibrate/train the model.

These concepts, even if usually referred to computational models, may apply to general models or representations of a system.

### 7.1.6 How to build a model

We need to define objectives:

- what do you want to model?

## 7.1. INTRODUCTION

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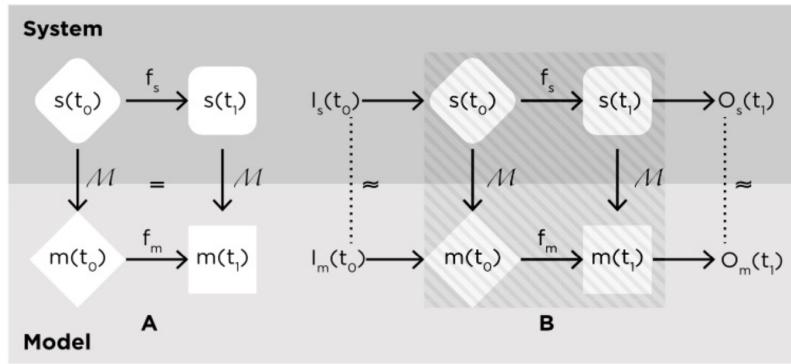


Figure 7.2: validation

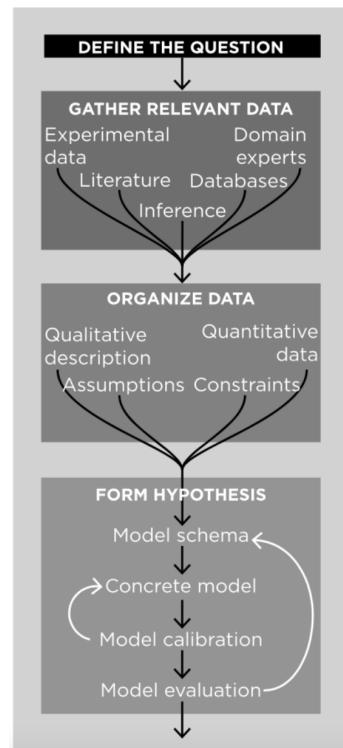
- what do you want to investigate with the model?
- what do you expect from the model?
- why do you need a model?

After defining the question and gathering data, we need to build the model and calibrate it, in order to check if it can recapitulate data. If it does not, either we are missing something or we must tune some parameters. Different parameters can lead to dramatic changes in dynamics. Example: Lotka-Volterra model with different parameter conditions (Figure 7.4).

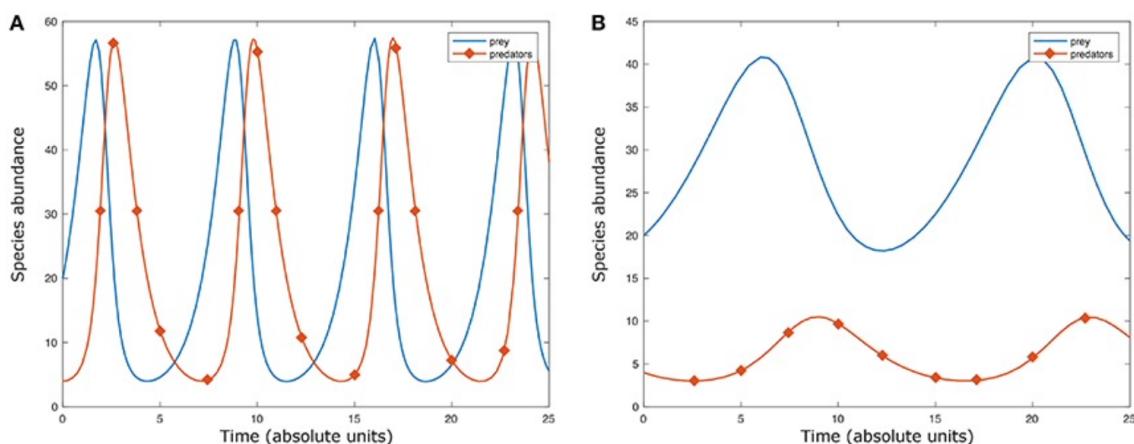
- A) shows periodic oscillations, same amount of preys and predators  
 B) wider peaks and lower predator presence

## 7.1. INTRODUCTION

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**Figure 7.3:** Workflow



**Figure 7.4:** Volterra

# Chapter 8

## Optimization problem

In general, it is a problem in which we try to *maximize* or *minimize* something. What we want to optimize is a function usually called *objective function* (or cost function). The function depends on a variable or a vector of variables, called unknowns or parameters or parameter estimates. They may be subject to certain constraints( $<$ , $>$ , $=$ ).

### 8.0.1 General definition of an optimization problem

$$\left\{ \begin{array}{ll} \max_{x \in \mathbb{R}^n} f(x) \\ c_i(x) = 0 & i = \mathcal{E} \\ f_j(x) \geq 0 & j = I \end{array} \right\} \text{set of indexes} \quad \left[ \begin{array}{l} \text{Constraints (equality and inequality)} \end{array} \right]$$

The model (for us) is a function that gives a certain interval/time, initial conditions and parameters, returns the variables at that time. (Assume deterministic description)

$$m : \mathbb{R} \times \mathbb{R}^{(n+1)} \times \mathbb{R}^m \rightarrow \mathbb{R}^N$$

where  $n+1$  accounts for the dimension of variables and time.

$$(t_1, (\vec{x}_0, t_0), \theta) \mapsto \vec{x}_1$$

Initial conditions in Lotka-Volterra:  $((20, 5), 0)$ .

$\theta$  represents parameters e.g. in Lotka-Volterra,  $a, b, \beta, \alpha$ . Now, assume that we have  $k$  observations:  $(t_i, \vec{y}_i), i = 1, \dots, k$ , where  $t_i \in \mathbb{R}^+$ ,  $\vec{y}_i \in \mathbb{R}^\ell$   $y$  in theory can be a subset,  $\ell < N$ : this happens a lot in complex systems, we may not observe all variables! For simplicity, we can assume  $\ell = N$ . Assuming that we can compute the following:

$$m(t_1, (\vec{x}_0, t_0), \theta) \in \mathbb{R}^N =_{\text{drop initial point notation}} m(t_1, \theta)$$

We can compute distance:  $d_i = \vec{y}_i - m(t_i, \theta)$ . We can choose any type of distance (Euclidean, max...). What we do is calculating point-wise the distance between the model and ‘true’ labels. It is quite common to use the **Euclidean distance**:

$$d\varepsilon = \sqrt{\sum_{i=1}^k (\vec{y}_i - m(t_i, \theta))^2} \rightarrow d\varepsilon = \sqrt{\sum_{i=1}^K \sum_{j=1}^N (y_{ij} - m_j(t_i, \theta))^2}$$

---

Sometimes we need to add weights, which multiply each component in the distances. We are putting together many outputs from the same model, so we might want to scale everything to make it more comparable. Furthermore, variables might be in different units of measurement, leading to biased results.

Observations:

- we do not want to reach “zero” when minimizing. Indeed, if the residual error = 0, we are 100% sure that we are overfitting the data.
- we need to really understand the data to construct the model
- we are manipulating  $\theta$  in the space of the parameters, but we modify the output in the space of the observations: we are connecting abstract values to observations - like parameters for maximum likelihood.

Weights are multiplicative factors, sometimes we might wish to *transform* the distance.

Example: **Least squares algorithm**

$$d\varepsilon = \sqrt{\sum \sum W_{ij} (y_{ij} - m_j(t_i, \theta))}$$

Our problem is to minimize/maximize a function. Assume:

$$\min f(x), x \in \mathbb{R}^n$$

### 8.0.2 Definition of a minimum

A point  $x^*$  is called **minimum** if  $\exists \varepsilon > 0 : \forall x : \|x - x^*\| < \varepsilon$

$$\Rightarrow f(x) \geq f(x^*)$$

[For the maximum  $f(x) \leq f(x^*)$ ]

The minimum is **global** if  $\forall x \in \mathbb{R}^n$  (or in our domain)  $f(x) \geq f(x^*)$ . In general it is not easy to determine global minimum/maximum, especially if we have a lot of dimensions. To find minima or maxima, we should impose  $f'(x) = 0$ .

We call a **stationary point**, a  $\bar{x}$  s.t.  $f'(\bar{x}) = 0$ .

# Chapter 9

## Gradient methods

When we integrate to find ODE solutions, we do not obtain a function as a solution, just points. In our optimization problem we do not know  $f$  and  $f'$  (only sometimes we do), so we are required to use *numerical approximation*. The idea of looking at  $f'$  and set  $f' = 0$  is still at the base of gradient methods.

If the problem contains constraints, how do we solve it? In this case the problem is:

$$\begin{cases} \max f(x) \\ g_i(x) = 0, \quad i \in \mathcal{I} \\ x \in \mathbb{R}^N \end{cases}$$

Let  $\mathcal{I} = 1, \dots, m$ . The traditional way to solve this problem is to translate this system to another function. The Lagrangian function is used to take into account the constraints.

### 9.0.0.1 Lagrangian function

We define the **Lagrangian function** as  $L : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}$  s.t.

$$L(x) = f(x) + \lambda g(x) = f(x) + \sum_{j=1}^m \lambda_j g_j(x)$$

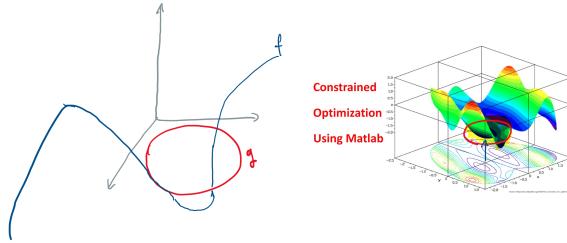
### 9.0.1 Lagrangian Multipliers Theorem

If  $x^*$  is a stationary point for (Lagrangian function), then  $\exists \lambda^*$  s.t.  $(x^*, \lambda^*)$  is a stationary point for  $L$ . It is a necessary condition (not sufficient, only one direction). This is a “bigger” problem, from  $\mathbb{R}^N \rightarrow \mathbb{R}^N \times \mathbb{R}^m$ . But still, I can search solutions using stationary points. We can generalize the idea to  $g_i(x) \leq 0$ , constraints

Remember that stationary points are not necessarily minima and maxima. We check whether a stationary point is a max/min through second derivations or evaluate the function in “other” points.

### 9.0.2 Definition of a gradient

Let  $f : \mathbb{R}^N \rightarrow \mathbb{R}$  a differentiable function, we call gradient of  $f$



**Figure 9.1:** Blue = function, red = constraint

$$\nabla f : \mathbb{R}^N \rightarrow \mathbb{R}^N \text{ sit. } \nabla f_i = \frac{\partial}{\partial x_i} f(x)_i \text{ and } \nabla f(x) = \begin{bmatrix} \frac{\partial}{\partial x_1} f(x) \\ \vdots \\ \frac{\partial}{\partial x_N} f(x) \end{bmatrix}$$

We look for points for which the derivative vanishes  $x^* : \nabla f(x^*) = 0$

$$\text{TRY at home: } f(x, y) = (1 - x)^2 + 100(y - x^2)^2$$

$$f(x, y) = -(y + 47) \sin(\sqrt{|x|/2 + (y + 47)|}) - x \cdot \sin(\sqrt{|x - (y + 47)|}).$$

These two functions are used to test optimization algorithms. The first is **Rosenbrock's function**, the second the **Eggholder function**. Solving analytically these problems is hard. We cannot apply gradient methods for stochastic simulations, since the function is not continuous.

### 9.0.3 Limitations of gradient descent methods

One of the major limitations of these algorithms is that we are focusing on local minima, we never know if the distance is minimum. Furthermore, sometimes we want to optimize more variables and it might not be optimal to perfectly fit the solution to both of them → trade-off.

Figure 9.1: if we have an equality constraint we are only considering the points meeting the boundary (red). In an inequality constraint, we consider everything inside the red circle (yellow area). Generally, constraints reduce our search space; the Lagrangian tells us that the minimum point with some multipliers will give a solution of the Lagrangian, which is one function. If we find the solutions, we do not know if they are solutions of the original conditions, but they are ideal candidates that can then be checked.

For performing an evaluation of the distance we should integrate the model, which is computationally expensive. To do one integration we must perform a lot of computations. Our measure of computational cost is the number of times we have to simulate the model (per iteration).

In most cases, we do not know the gradient, therefore we should approximate it using the Taylor formula.

### 9.0.4 Gradient approximation with Taylor formula

$$(a, b) \in \mathbb{R}, x_0 \in (a, b)$$

---

Let  $f_i(a, b) \rightarrow \mathbb{R}$  be differentiable  $(n - 1)$  times in  $(a, b)$  and  $f^{(n)}$  is continuous in  $x_0$ . Then let  $x \in (a, b)$ , we have:

$$f(x) = f(x_0) + f'(x_0)(x - x_0) + f''(x_0) \frac{(x - x_0)^2}{2!} + \dots + f^{(n)}(x_0) \frac{(x - x_0)^n}{n!} + R_n(x) \text{ s.t. } \lim_{x \rightarrow x_0} \frac{R_n(x)}{(x - x_0)^n} = 0$$

We focus on the first terms  $f(x) = f(x_0) + f'(x_0)(x - x_0) + R_2(x) = 0$

$$f'(x_0) = \frac{f(x) - f(x_0)}{x - x_0} + \left( \frac{R_2(x)}{(x - x_0)} \right) = \frac{f(x) - f(x_0)}{x - x_0} + R_1(x).$$

We can also use this trick for  $N > 1$

Let  $f : \mathbb{R}^N \rightarrow \mathbb{R}$  and  $e_i = (0, \dots, 0, 1, 0, \dots, 0)$ . Let's consider  $x_1 x + \varepsilon e_i, x - \varepsilon e_i$ ; we are only moving along one direction. In this case:

$$f(x + \varepsilon e_i) = f(x) + \varepsilon \frac{\partial f}{\partial x_i}(x) + \frac{1}{2} \varepsilon^2 \frac{\partial^2 f}{\partial x_i^2}(x) + R_3(x) \\ f(x - \varepsilon e_i) = f(x) - \varepsilon \frac{\partial f}{\partial x_i}(x) + \frac{1}{2} \varepsilon^2 \frac{\partial^2 f}{\partial x_i^2}(x) + R_3(x) \Rightarrow f(x + \varepsilon e_i) - f(x - \varepsilon e_i) = 2\varepsilon \frac{\partial f}{\partial x_i}(x) + \varepsilon^2 \frac{\partial^2 f}{\partial x_i^2}(x)$$

We have computed an approximation of the first derivative with improved accuracy.

Consider that this only applies to one derivative, we have to perform this at least twice  $\rightarrow 2$  function evaluation for each  $i \Rightarrow 2W$ . In order to obtain a decent gradient, we require a lot of computations, but they are fast (quite low number of iterations). We will see other methods, which are somehow more precise, but also heavier.

We can always check  $\Delta f = 0$  or not to understand if we are done!

As we already saw, there might be points where the gradient vanishes which are not the final destination. Gradient methods may tend to overfitting, but they are effective. The main issue is that since we approximate the gradient, we do not trust it everywhere.

Gradient methods can be applied to two different categories of problems:

- constrained
- unconstrained
  - **line search algorithm:** follow a direction
  - **trust region:** create an approximation of the problem and solve it in a small trustable region

## 9.0.5 Line search

### 9.0.5.1 Newton's direction

If we consider Taylor's formula and let  $x_k$  be our starting point, let  $\alpha \in \mathbb{R}^+$  step length and  $p$  our direction ( $x_k, p \in \mathbb{R}^n$ ). For  $n = 1$ , we have:

$$f(x_k + \alpha p) = f(x_k) + \alpha p f'(x_k) + \frac{\alpha^2 p^2}{2} f''(x_k) + r(p^3)$$

For simplicity set  $\alpha = 1$  and truncate the formula:

---


$$f(x_n + p) = f(x_n) + pf'(x_n) + \frac{p^2}{2}f''(x_n) = m_k(p)$$

→ instead of minimizing the initial  $f$ , we minimize the simple polynomial  $m_k(p)$ . From this equation we can get the direction  $p = -\frac{f'(x_k)}{f''(x_k)}$ , which is called *Newton direction* (best direction). When  $n > 1$ ,  $p = -(\nabla^2 f(x_k))^{-1} \nabla f(x_k)$ . Finding the inverse of a matrix is “a pain”, not straightforward; this is why we will try to approximate this part.

#### 9.0.5.2 Line search algorithm for function minimization

Set  $k = 0$  and guess an initial point  $x_0$  WHILE  $\|\nabla f(x_k)\| > 0$

1. compute  $p_k = -(\nabla^2 f(x_k))^{-1} \nabla f(x_k)$
2. select  $\alpha_k$
3. update  $x_{k+1} = x_k + \alpha_k p_k = x_k - \alpha_k (\nabla^2 f(x_k))^{-1} \nabla f(x_k)$
4.  $k = k + 1$

We stop when the gradient is equal to zero, but we do not really have zeroes in our computers; therefore, we must apply a threshold  $\varepsilon$ .

At each iteration we have some issues:

- sometimes we require approximation to compute the inverse of a matrix
- it is computationally expensive to compute all these gradients

Nevertheless, going in this direction is smart. We can try to tackle the hardest part, i.e.  $p_k$  computation, by approximation.

#### 9.0.5.3 Quasi Newton's direction

To avoid the computation of  $\nabla^2 f$ , we build iteratively a different matrix  $B_k$ , such that  $B_{k+1} \cdot (x_{k+1} - x_k) = \nabla f(x_{k+1}) - \nabla f(x_k)$  [condition for the matrix]

We are approximating the second derivative as second of the gradient. Since we are already computing the gradient, we exploit it to prevent extra computations. The difference with respect to standard Newton direction is the Hessian, which is not computed here.

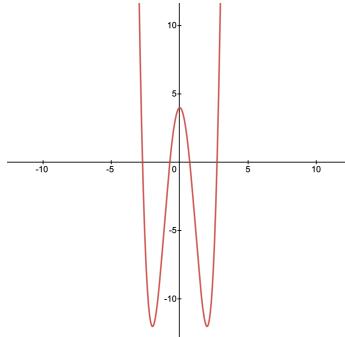
**Quasi-Newton direction:**  $P_{k+1} = -\alpha B_{k+1}^{-1} \nabla f(x_k + 1)$

#### 9.0.5.4 Steepest descent direction

We proceed in the direction that reduces the gradient the most:

$$p = -\alpha \frac{\nabla f}{\|\nabla f\|}$$

In this case we are completely ignoring the second derivative, we only focus on the gradient computation. This method converges slowly with respect to Newton and Quasi-Newton's direction.



**Figure 9.2:** Desmos  $f(x) = x^4 - 8x^2 + 4$

#### 9.0.5.5 Selecting $\alpha$

Ideally, we want to define  $\alpha$  s.t.

$$\bar{\alpha} = \arg \min_{\alpha > 0} f(x_k + \alpha p)$$

This is another optimization problem, ideal situation. To avoid solving the optimization, we usually consider  $\alpha$  that satisfies :

$$f(x_k + \alpha p) \leq f(x_k) + c_1 \alpha \nabla f(x_k)^T p_k, c_1 \in (0, 1)$$

**Armijo condition:** the reduction should be proportional to  $\alpha$  and  $\nabla f(x_k)^T p_k$ . Sometimes thing fails because of parameter choice: it is crucial to understand why functions fails and how parameters tuning can affect the most crucial steps in the algorithms.

#### 9.0.5.6 Convergence of a method

The order of convergence of a method (for us) is a constant  $\ell$ , such that exists the limit:

$$\lim_{k \rightarrow \infty} \frac{\|f(x_{k+1}) - f(x^*)\|}{\|f(x_k) - f(x^*)\|^\ell} = L > 0$$

Where  $x^*$  is the solution and the method converges.

We compare the new iteration (numerator) to the old iteration (denominator); the limit should go to zero, the exponent is the speed - the higher the exponent  $\ell$ , the faster will the upper term go to zero with respect to the bottom one i.e. faster convergence. The higher the exponent, the less iterations are required (in general). For the methods that we have previously seen:

- steepest descent:  $\ell = 1$ , linear convergence
- quasi-Newton:  $\ell \in (1, 2)$ , superlinear convergence
- Newton:  $\ell = 2$ , quadratic convergence

Example:  $f(x) = x^4 - 8x^2 + 4$

$$x_0 = 3f'(x) = 4x^3 - 16x \Rightarrow f'(x) = 0 \Rightarrow x = 0, x = \pm 2, f''(x) = 12x^2 - 16$$

Algorithm:  $f'(3) = 60, f''(3) = 92,$

---

Let  $\alpha = 1$ :

$$p_0 = -\frac{60}{92} = -0.65x_1 = 3 - 0.65 = 2.35 f'(2.35) = 14.31 f''(2.35) = 50.27 p_1 = -\frac{f'(x_1)}{f''(x_1)} = -0.28x_2 = x_1 + \alpha p_1 = 2.35 - 0.$$

Let's try the same by applying Steepest Descent method:

$$f'(3) = 60$$

$x_1 = x_0 \dots f'(3) = 60$  In this case the SDM is way faster, lucky shot. But what if we change the starting point? The direction will always be the same, i.e.  $p_1 = -1$ .

$$x_1 = 2.35 - 1 = 1.35 f'(x_1) = -11.75 x_2 = 1.35 + 1 = 2.35$$

We are doing ping-pong among two points!

The fact that the second derivative progressively shrinks tells us that we need to reduce the step, but in this case we are not taking this into account. Of course we also have  $\alpha$ , we should look at Armijo condition and change it. Take into account that each time that we are performing operation on a number we lose precision.

### 9.0.6 Trust region

[picture] Imagine that this is a cut function: our starting point  $x_k$  is in the middle. The main idea of the trust region is that we do not follow a direction: we approximate the function with a simpler function  $\rightarrow$  Taylor approximation. According to how big and reliable the approximation is, we will choose a direction.

Last time we approximated the model as:

$$\begin{aligned} m(x_p + \alpha p) &= f(x_k) + \alpha p^T \nabla f(x_k) + \frac{1}{2} \alpha^2 p^T B_k p \\ \alpha = 1, m_k(p) &= f_k + p^T \nabla f_k + \frac{1}{2} p^T B_k p \end{aligned}$$

#### 9.0.6.1 Trust region steepest descent

Define a region such that  $\|p\| < \delta_k, \delta_k > 0$  in which we solve the optimization problem (1) instead of the original. Remember that  $B_k$  can be the Hessian or an approximation; on the other hand, we have said that we can also ignore it.

Finding a minimum for  $m_k(p) = f_k + p^T \nabla f_k$  means that we are looking for:

$$\min_p m_k(p) = \min_p (f_k + p^T \nabla f_k)$$

Remember that  $f_k$  is a constant, so we want to find a direction for which  $\min_p p^T \nabla f_k$  is minimum. We can rewrite this as:

$$p^T \nabla f_k = \|p\| \|\nabla f_k\| \cos \theta$$

We minimize for  $p$  such that  $\cos \theta = -1$  and  $\|p\| = \delta_k$ , where  $p$  s.t.  $\|p\| \leq \delta_k$  [radius of the trust region].

---


$$\min_p p^T \nabla f_k = -\delta_k \|\nabla f_k\|$$

$$p = -\delta_k \frac{\nabla f_k}{\|\nabla f_k\|}$$

This result is exactly the equation from steepest descent. We are applying a condition on the region with  $\delta_k$ . This direction and the whole approach is called trust region steepest descent.

We could follow the same idea by applying Newton or Quasi-Newton.

To evaluate if we can really trust our region, we define the *actual reduction* as:

$$\rho_k = \frac{f(x_k) - f(x_k + p)}{m(x_k) - m(x_k + p)}$$

By construction  $m(x_k + p) \leq m(x_k)$ .

- If  $\rho_k < 0 \rightarrow$  reject  $p$ , we are not improving the real problem. Usually take  $\delta_k = \frac{1}{4}\delta_k$
- If  $\rho_k \simeq 1 \rightarrow$  maybe longer step

$\delta$  value can be tuned according to the needs. The approach is similar to RK method seen with Marchetti. Of course we have a grey area between 0 and 1, so we define a threshold e.g.  $\rho_k < \eta$  and  $\rho_k > \eta$ . By default, MATLAB uses a trust region algorithm. Having something certifying that we are doing good or bad is a great thing in approximation!

#### 9.0.6.2 Trust region algorithm

Let  $\hat{\delta} > 0, \delta_0 \in (0, \hat{\delta}), \eta \in (0, \frac{1}{4})$

$k = 0, \varepsilon < 0$

REPEAT

obtain  $p_k$  s.t.  $p_k = \arg \min_p m(x_k + p)$

compute  $\rho_k$

IF  $\rho_k < \frac{1}{4}$

$\delta_{k+1} = \frac{1}{4}\delta_k$

ELSEIF ( $\rho_k < \frac{3}{4}$ ) AND  $\|p_k\| = \delta_k$

$\delta_{k+1} = \min(2\delta_k, \hat{\delta})$

ELSE

$\delta_{k+1} = \delta_k$

IF  $\rho_k > \eta$

$x_{k+1} = x_k + p_k$

ELSE

$x_{k+1} = x_k$

IF  $\|\nabla f(x_{k+1})\| < 0$

BREAK

We stop if the gradient is sufficiently small. Our focus is on computing  $p_k$ . We then evaluate  $\rho_k$  to adjust parameters (which is simpler from what we have previously seen).

If we apply this algorithm to the example of last lecture, it happens that with  $x_0 = 235$  and

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steepest descent  $\rho_0 = 0.17 < \frac{1}{4}$ , which tells us to reduce  $\delta$ . The only thing that changes is  $\rho$  changes.

PROBLEM:

$$g(x, y) = x^4 + y^4 + xy$$

<https://www.benfrederickson.com/numerical-optimization/> play with learning rate, explore the site.

# Chapter 10

## Least squares problems

Recall that if  $m$  is the model, we quantified the distance between the model output and data as:

$$m_j(t_i, (x_0, t_0), \theta) = m_{ij}(\theta) - \hat{y}_{ij}, \text{ for } i, j \text{ as lesson 2}$$

$r_{ij}(\theta)$  is called RESIDUAL and we shape it as a vector.

$$J_k = J(\theta_k) \left[ \frac{\partial r_I}{\partial \theta_i} \right], i = 1, \dots, n, I = 1, \dots, n$$

Since the time points are given by the data, everything only depends on the choice of parameter theta, which is a vector of parameters. We can derive the residual according to theta. Our function to minimize is  $f(\theta) = \frac{1}{2} \sum_{j=1}^m r_j^2(\theta)$ . It will hardly go to zero, as our observations are affected by noise: we just need to explain data, not noise. If we have the distance of the single point we can see the effect of each parameter by looking at the derivative. Here we have that the gradient (Jacobian) will be telling us the relationship among model parameters and data.

$$\nabla f(\theta) = \sum_{j=1}^m r_j(\theta) \nabla r_j(\theta) = J(\theta)^T r(\theta)$$

The matrix notation is a more convenient way to express this gradient. While solving least squares problems we always exploit Taylor approximation.

Hessian matrix:

$$\nabla^2 f(\theta) = J^T(\theta) J(\theta) + \sum_{j=1}^m r_j(\theta) \nabla^2 r_j(\theta)$$

What's *magical* of this is that we can use  $J^T(\theta) J(\theta)$  as approximation for  $B(\theta)$  of our gradient.

If the problem is linear,  $r(\theta) = A(\theta) - y$ . The objective function  $f(\theta) = \frac{1}{2} \|A\theta - y\|^2$  and  $\nabla f(\theta) = A^T(A\theta - y)$ ,  $\nabla^2 f(\theta) = A^T A$ .

If  $f$  is convex  $\Rightarrow \exists \theta^* s.t. \nabla f(\theta^*) = 0 - A^T A \theta^* = A^T y$

We reach a normal equation, linear system (we know how to solve this). With general functions, this is not so straightforward; what we will do is approximating the problem with a solvable linear

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problem.

When we try to quantify the distance between the model and our points we can formalize the problem as:

$$r_i = m_i(t, \theta) - y_0 f(\theta) = \frac{1}{2} \sum_{j=1}^m r_j^2(\theta) \nabla f(\theta) = J(\theta)^T r(\theta) \nabla f(\theta) = J(\theta)^T J(\theta) + \sum_{j=1}^m r_j \theta \nabla^2 r_3 \theta$$

Last time we already said that we will ignore the sum, for two reasons:

1. it contains second order derivatives, painful to compute
2. the Newton direction is a quasi vector

So at every iteration  $k$  we solve the approximated problem

$$J(\theta_k)^T J(\theta_k) p = -J(\theta_k) r(\theta_k) J_k^T J_k p = -J_k^T r_k$$

This is a linear system which we can solve. In this case, we are solving:

$$f(\theta_k + p) = \frac{1}{2} \|r(\theta_k + p)\|^2 \simeq \frac{1}{2} \|J_k p + r_k\|^2$$

This is what we called normal equation for a normal least squares problem. Under certain hypotheses the method converges quadratically!

We discussed last time that Newton is quadratic convergent. Of course the matrix should not be singular, we need to be able to solve the system. We start with a problem in a special form, sum of squares. Thanks to this, we can rewrite the problem in a simpler way and perform an approximation, leading to solving a linear system at each iteration. This approximation guides us rapidly to a solution. We are applying linear search, by defining a direction and solving a new problem at each iteration. The biggest issue could be the non invertible matrix, but we can do something to circumvent the issue.

### 10.0.1 The Levenberg-Marquardt method

At each iteration, we solve the problem:

$$\min_{\|p\| \leq \delta_k} \frac{1}{2} \|J_k p - r_k\|^2$$

We can have a solution inside the trust region  $\delta_k$  or on the border i.e. not the minimum, but the smallest value we can reach.

- case 1:  $\beta$  is a solution and  $\|p\| \leq \delta_k \rightarrow \text{DONE}$
- case 2:  $\|p\| = \delta_k$ , then  $\bar{p}$  is a solution if and only if  $\exists \lambda > 0$ :

$$(J^T J - \lambda I) = -J^T r + \lambda(\delta_k - \|p\|) = 0$$

If we can push it a bit further from zero and the problem is still solved, we can think of it as a solution. If we are hitting the boundary  $\lambda(\delta_k - \|p\|) = 0$ , we want to move the matrix a bit from singularity. We will not use it very much, but it is a well known algorithm. It is one of the default MATLAB solvers. The Levenberg-Marquardt converges quadratically when we are close to the solution, while if the residuals are big it does not perform well.

---

### 10.0.2 Solving a problem with bounds

We have seen together that we can exploit the Lagrangian for the equality constraint, but we can have other boundaries. There are other approaches which allow us not to lose our approximation advantage. We can simply do **variable transformation**: instead of changing the problem, we change the variables. Example:  $x \rightarrow e^x$ ,  $\mathbb{R} \rightarrow \mathbb{R}_0^+$  [other example missing, cannot understand from recording]

Another solution could be to include the bound in the **trust region**.

[drawing missing] *Evolutionary algorithms* follow the evolution of the solution: at the beginning look for solutions, then add a penalty for the boundaries.

### 10.0.3 Solving global minimum problem

How can we be sure that we are looking at a global minimum? We can start from another initial point and check whether the solution reaches the same minimum. From local to global  $\rightarrow$  the **multi-start approach**, t is a shortcut, but the best way to work.

### 10.0.4 Gauss-Newton method

Let  $N \in \mathbb{N}$ ,  $\varepsilon > 0$ ,  $J$  as defined before. We randomly select  $N$  vectors and use  $\theta^1, \dots, \theta^n \in \mathbb{R}^n$

For each  $i = 1, \dots, N$  DO

REPEAT

$\bar{J} = J(\theta^i)$

compute  $q$  s.t.  $\bar{J}^i \bar{J} q = -\bar{J} r(\theta^i)$

compute  $\vartheta = \theta^i + q$

compute  $\varepsilon = \left\| \frac{\theta^i - \vartheta}{\theta} \right\|$ , relative increase

update  $\theta^i = \vartheta$

IF  $\varepsilon < \bar{\varepsilon}$  then BREAK

SAVE  $\theta^i$

END

$\rightarrow$  no global minimum guarantee!

There are other ways to detect if a minimum is global e.g. we try to divide the space in  $N$  different sectors and pick points for each one of them, *Latin hypercube* and *orthogonal sampling*. The more we do it, the more we acquire confidence, but we will never be sure. In addition, we always have to deal with noise, we do not know if the minimum is the best or we are overfitting.

Example on MATLAB: if we take only 10 random points we can have a biased result. By taking a bigger sample, we should somehow achieve a fuller result in the region. Still, we have some holes and repeated points. Are there smarter ways to take random points?

### 10.0.5 Latin hypercube sample

Get random numbers dividing the interval in  $m$  sectors. This is a 2x2 problem and we need to reason on some aspects: if we take the square  $(0,1), (0,1)$  out of 100 points we will just have  $3/4$  there  $\rightarrow$  not exploring it very well. If parameters are between 0.1 to 1000 we need to better sample.

$n = 20$ , the fewer points we get, the more we see the difference among the two methods.

$n = 200$ , still we have missing parts.

---

$n = 2000$ , thousands of iterations → if we zoom in there is still a lot of space

The takehome message is that it is almost impossible to cover all the space with points. Luckily these are starting points, if they are close to the solution we will have the good direction. Gradient methods are expensive, but they are smart.

### 10.0.6 MATLAB

When an optimizer stops, it gives as output the function converged to the solution or why it stopped. Termination criteria: gradient, incremental step e.g. is our step too small?, change in  $x$  was less of certain tolerance, the residual was less than specific tolerance, max number of iterations. These conditions are added in order to avoid infinite function evaluation.

We first need to define an enzymatic reaction as a set of ODEs. We then specify initial concentrations and a given set of rates. Integrate the model and plot the simulation results.

The dots are the experimental points, lines are the output of the simulation. According to different starting points, we will obtain different results; we need to quantify how much the model is distant from the real data. The output of the normal simulation is a set of points; we can do a linear interpolation for time and values, giving how much is each of the simulated variables at the requested time. Once we have the values at the right time, we can compute the *residuals* through the sum of squares. In some cases we can also look at weighted residuals and normalize them; however, zeros are problematic → our experimental data goes to zero, we stick to normal SSE.

Our objective function takes the rate, experimental time and values, initial and final time. We call the solver (15s as the system is stiff, we require a more robust iteration) and get a vector of residuals and SSE.

If we compute the residual with  $s_1, s_2$  and  $s_3$  we can easily understand which is the better one (matches visual inspection of the plot).

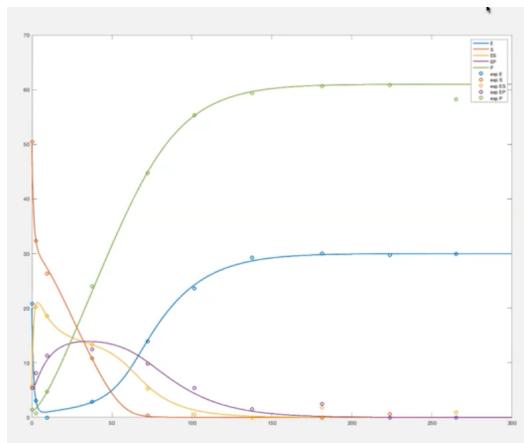
We can then optimize and find the solution with `lsqnonlin` e.g.  $SSE1 = 33.6653$ ,  $resNorm = 38$ , worse, we should improve initial conditions.

[Recap from last time]

**MATLAB multi-start** is a wrapper working with different algorithms. It will automatically parallelize the problem. It requires to insert starting points and tolerance. We therefore define bound, create problem and give initial points e.g. `lsqnonlin + objective function`. The output contains the result of parallel `lsqnonlin` and parameters, somehow similar to what we saw before. We can reduce the bounds, but solution 1 is still the best. Main limitation: heavily depends on the number of initial points.

Remarks:

- we did a lot of computations
- $s_1$ , the initial set of parameters, had values at different orders of magnitude. We really do not know if we are doing well or not.



**Figure 10.1:** MATLAB multi-start lsqnonlin

## Chapter 11

# Stochastic methods for parameter estimation

Stochastic methods are often used when we cannot compute the gradient. With the same parameters, stochastic methods can produce dramatically different results.

Lotka-Volterra stochastic simulation results are reported in Figure 11.1- In B we witness preys and predators extinction, it is the output of a simulation performed with the same model and parameters as A.

Instead of following the gradient, we collect information in a manner resembling natural selection. Monte Carlo Methods are dated around 1949, the name comes from casinos (recalls concept of luck). In order to use MCMC to do inference, Metropolis and Hastings developed a specific algorithm in 1970.

### 11.0.1 Markov Chain Monte Carlo (MCMC)

MCMC is a chain of events where the current state depends on the previous one and on the transition probability. If  $x^{(i)}$  is a random variable (stochastic process) and it takes only discrete values  $\{x_1, \dots, x_s\}$ . Let  $p(x)$  be the probability distribution of  $x$ .  $x^{(i)}$  is a Markov Chain if:

$$p(x^{(i)} | x^{(i-1)}, \dots, x^{(1)}) = T(x^{(i)} | x^{(i-1)})$$

Simplest case: a MC is **homogenous** if  $T(x^{(i)} | x^{(i-1)}) = T$ , i.e. the transition matrix is constant.

If we run MCMC long enough, they will hopefully reach a stable point.

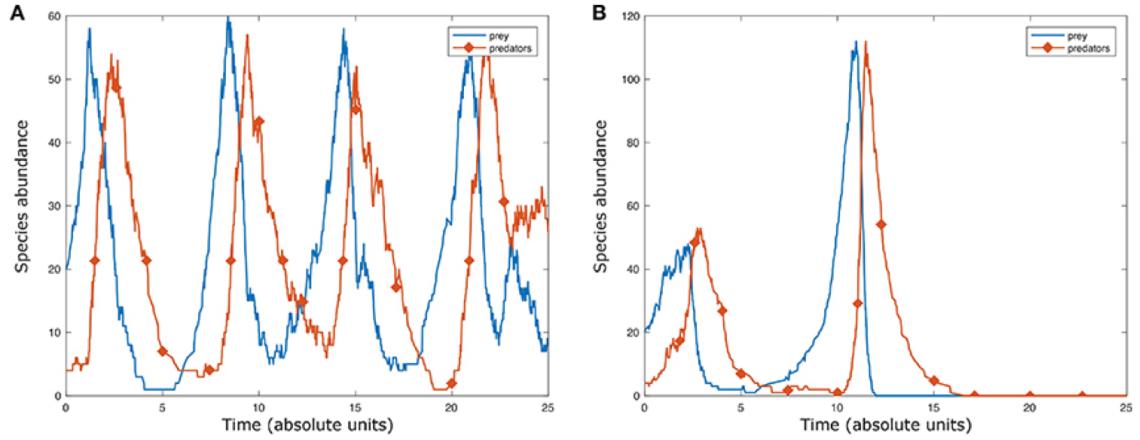
Example: 3 states and homogenous transition matrix

$$T = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0.1 & 0.9 \\ 0.6 & 0.4 & 0 \end{bmatrix}$$

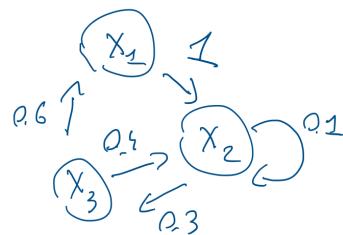
MCMC example (Figure 11.2):

$$\pi_1 = (0.5 \quad 0.2 \quad 0.3)$$

The next probability of being in the three states is given by



**Figure 11.1:** Lotka-Volterra stochastic simulation results. In B we witness preys and predators extinction, it is the output of a simulation performed with the same model and parameters as A.



**Figure 11.2:** MCMC example

$$\pi_1 \cdot T = (0.3 \cdot 0.6, \quad 0.5 + 0.02 + 0.12, \quad 0.18) = (0.18, \quad 0.64, \quad 0.18)$$

If we do this enough, we will always arrive to a fixed distribution, called invariant distribution  $\Rightarrow$  we want to build a Markov Chain whose invariant distribution is the distribution of our unknown parameters.

$$p(x) = \dots = \begin{pmatrix} 0.2213 \\ 0.4098 \\ 0.3689 \end{pmatrix}^T$$

Where  $p(x)$  is called **invariant distribution**.

A stochastic matrix is *irreducible* if its graph does not contain unconnected sub-graphs. If  $T$  is an irreducible transition matrix (+ aperiodic)  $\rightarrow$  the MC has an invariant distribution. We must connect probability distribution / values for the parameters with the model. There is a known function that we can use to do so.

Monte Carlo refers to a family of methods developed for **sampling**. In particular, we obtain samples of a certain i.i.d. random variables  $\{x^{(i)}\}_{i>0}$  from a known density  $p(X)$ .

The samples can be used to “estimate / approximate” a target density / distribution. We exploit known distributions e.g. Normal, Poisson, ... to approximate our unknown distribution of interest.

Given enough samples, we can approximate  $p$  as:

$$p_N(x) = \frac{1}{N} \sum_{i=1}^N \delta_{x^{(i)}}(x)$$

with  $\delta_{x^{(i)}}(x) = \begin{cases} 1, & x = x^{(i)} \\ 0, & \text{elsewhere} \end{cases}$  This is often used to approximate “hard” integrals. We can approximate an integral with a finite sum of values, which is obtained as:

$$I_N(f) = \frac{1}{N} \sum_{i=1}^N f(x^{(i)})$$

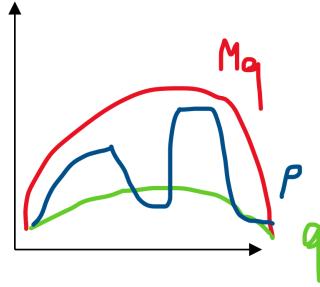
Here we are evaluating the function at some points. We can use the mean as an approximation of the integral. This equation converges to the real integral by the law of large numbers.

$$I_N(f) = \frac{1}{N} \sum_{i=1}^N f(x^{(i)}) \xrightarrow{N \rightarrow \infty} I(f) = \int_x f(x)p(x)dx$$

A probability is richer than the output of one least squares, we have information on the shape.

### 11.0.2 Sampling a distribution

Let  $p$  be a known probability distribution (up to a proportionality constant). We usually prefer to sample from a well-known distribution  $q(x)$  s.t.  $\exists M > 0$



**Figure 11.3:** Example: bimodal distribution

$$p(x) \leq Mq(x)$$

We extract values from  $q$  if they are smaller than  $Mq$ ; each time we are collecting information on  $p$  collecting from  $q$ .

### 11.0.3 Rejection sampling algorithm

```

Set  $i = 1$ 
REPEAT
  Sample  $x^{(i)}$  from  $q$  and  $u \in \mathcal{U}(0, 1)$ 
  IF  $u < \frac{p(x^{(i)})}{Mq(X^i)}$  and  $x^{(i)}$ 
     $i = i + 1$ 
  ELSE
    REJECT
  
```

If the point is in the area between  $p$  and  $Mq$  we still accept it; the further the ratio is from one, the smaller the chance of keeping the point.

At this point we are using a known distribution  $p$ ; we then gradually remove what we know in the following iterations.

### 11.0.4 Metropolis Hastings

Let  $X$  be our current point,  $q$  the proposal distribution and  $p$  the target distribution.  $p$  can be an unnormalized density ( $\int p > 1$  but  $\int p < \infty$ ). Ideally we want to know  $p$ , but if it is unknown we can still proceed. Let us call this function  $h$  (non negative and positive integral).

$X^*$  is the new candidate point. The trick of MH algorithm is to avoid relying on probability, we use a function. We require info on  $p$ , but not a probability.

**Metropolis ratio**  $r_M(x, x^*) = \frac{h(x^*)}{h(x)}$

**Hastings ratio**  $r_H(x, x^*) = \frac{h(x^*) \cdot q(x|x)}{h(x) \cdot q(x|x^*)}$  From the distribution, we want to measure how likely the previous value is based on the current value. We are weighting our choices to likeliness.

---

#### 11.0.4.1 MH algorithm

Guess  $x^{(i)}$

```
FOR i = 0 to N - 1
    Sample  $x^*$  from  $q(\cdot|x^{(i)})$  and  $u \in \mathcal{U}(0, 1)$ 
    IF  $u < \min\{1, r_H(x, x^*)\}$ 
         $x^{(i+1)} = x^{(*)}$ 
    ELSE
         $x^{(i+1)} = x^{(i)}$ 
    END
END
```

We sample from a proposal distribution and accept according to another function i.e. if it is more likely. If it is not more likely, we accept it with a certain chance.

MATLAB plot:

- right: histogram with the known distribution
- left: MCMC oscillating between 0 and 10, recapitulates the distribution

The procedure is really fast, takes less than a second. If instead of extracting u and v from random distribution with an index, the result is the same → “thanks MATLAB, it is not necessary to pre-locate anymore”

If we employ a Gaussian distribution, the result is still good but not as accurate as the previous one. We are adding complexity by introducing the variance; by choosing a different value we can improve the result. Pay attention to the fact that if we sample from a narrow distribution, we risk focusing only on one of the two points.

Everything we do has consequences!

#### 11.0.4.2 Visualization of MCMC

<http://chi-feng.github.io/mcmc-demo/app.html?algorithm=RandomWalkMH&target=banana> Green: accept, red: reject

Target distribution = standard

- GibbsSampling: collects points according to a certain direction from a starting point, it tries to rebuild a 2D Normal distribution.
- AdaptiveMH: sample from a starting mean and accept or reject new points.
- Random walk: more or less like MH. Even if the target distribution is not that difficult (bell shape), there are a lot of rejections initially.
- DE-MCMC-Z: produces vectors.

Target distribution = donut

- SVGO: stochastic vector gradient descent, intermediate between gradient and stochastic.
- EfficientNUTS (No-U-Turn samples): it creates many points, more complex but one of the best. In the end it will converge quite fast.

- 
- RandomWalk: needs more time to converge with respect to standard distribution.

Target distribution = multimodal

- RandomWalk: three initial points, it proposes a random perturbation.
- AdaptiveMH: changes some of the parameters. Differently from the previous approach, the shape changes: instead of having a fixed search area, it evolves and adapts.

#### 11.0.4.3 How to link data and MH

In LSQ, we used the function

$$f(\theta) = \frac{1}{2} \sum_{j=1}^m r_j^2(\theta) = \frac{1}{2} \sum_{j=1}^m (y_j - m_j(t_i, \theta))^2$$

We can weight our residuals for their uncertainty:

$$f_w(\theta) = \frac{1}{2} \sum_{j=1}^m \frac{r_j^2(\theta)}{\vartheta_j^2}$$

$\vartheta_j$  = (for example) the standard deviation of that measured point.

We can use as function to link the parameters and the output, and be non-negative: [where  $Y$  is the vector of our observations]

$$L(\theta|Y) = \exp(-f_w(\theta)) \geq 0$$

We can use this as  $h$  in the MH algorithm.

Metropolis ratio:

$$r_H(\theta^*, \theta) = \frac{L(\theta^*)}{L(\theta)} = \frac{e^{-f_w(\theta^*)}}{e^{-f_w(\theta)}} = \exp(-f_w(\theta^*) + f_w(\theta))$$

So since  $f_w(\theta) \geq 0$  we have that if  $f_w(\theta^*) > f_w(\theta) \Rightarrow r_H > 1$ , we ACCEPT. Otherwise we accept with a certain probability. This kind of function can be used to link the new parameters with data. We can work with log-likelihood also here, we just look at  $f_w(\theta^*)$  and  $f_w(\theta)$ .

#### 11.0.5 Random walk MCMC

Let us assume  $\theta^*$  is sampled from  $\mathcal{N}(0, \mathcal{C}) + \theta = \mathcal{N}(\theta, \mathcal{C})$

We add a perturbation with  $\mathcal{C}$ , a known covariance matrix.  $\mathcal{C}$  can be fixed or adapted along the iterations.

From the initial point we have a new candidate according to a multivariate normal distribution; if the candidate is accepted, we will then restart evaluation from it. We are collecting some information allowing us to shape the target distribution.

---

#### 11.0.5.1 Algorithm RW-MCMC ( C known)

Initialize a matrix  $D_\theta$  and a vector  $V_L$

Randomly generate  $\theta_1$

Compute  $L(\theta_1) = L_1$

For  $i = 1 : N$

sample  $Z \sim N(D, \mathcal{C})$

compute  $\theta_2 = \theta_1 + Z$

compute  $L_2 = L(\theta_2)$

compute ratio =  $\frac{L_1}{L_2}$

sample  $u \sim \mathcal{U}(0, 1)$

IF  $u < \text{ratio}$

$L_1 = L_2$

$\theta_1 = \theta_2$

END

IF  $i >$  warm-up

$D_\theta = [D_\theta; \theta_1]$

$V_L = [V_L; L_1]$

END

END

We want to find a good accept-reject tradeoff to reach a satisfactory convergence.

#### Pros

- the object function is evaluated once per iteration
- the target distribution can be built from the samples
- we only need the last point to restart
- we can collect info on the model: variability on the output + sensitivity on parameters
- random selection helps us to avoid local minima

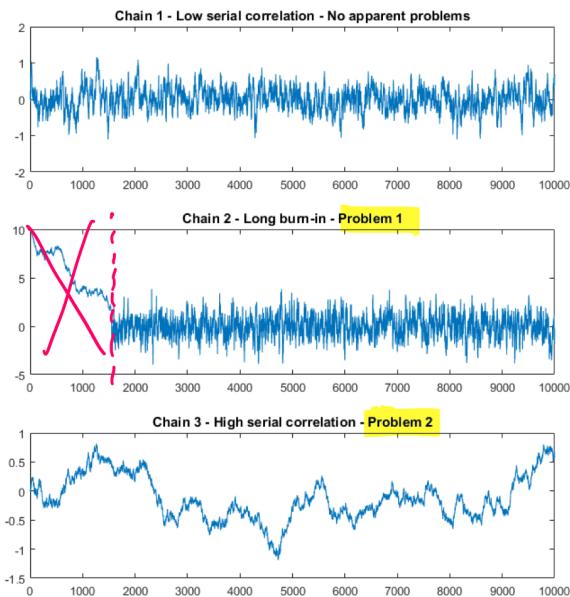
#### Cons

- convergence may be slow
- sampling distribution may affect the results
- each MCMC cannot be parallelized
- burn-time
- diagnostics are heuristics

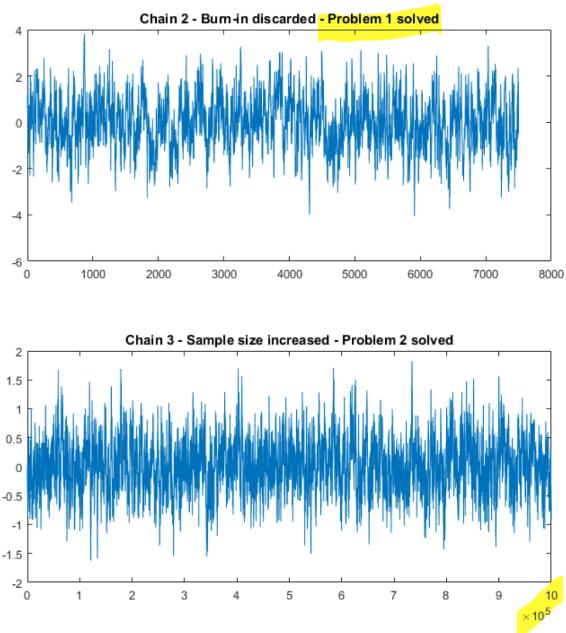
#### 11.0.5.2 Diagnostics

We can exploit diagnostics to check if the parameters are good and understand whether we are done or not.

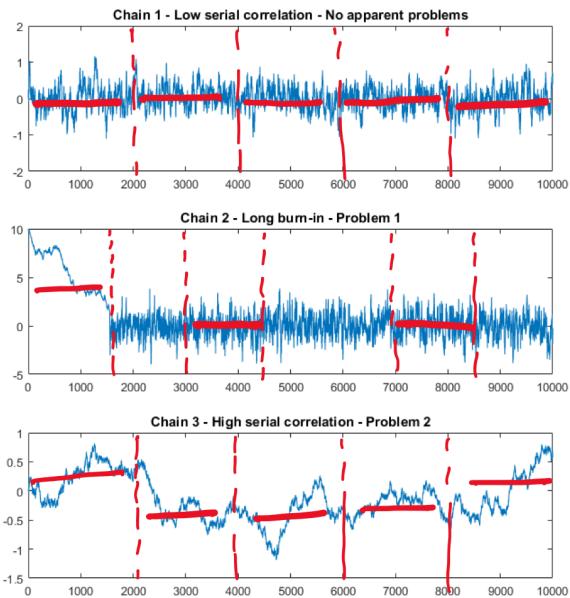
1. chain 1: expected MCMC plot
2. chain 2: we require a longer burn-in, we have not reached the target distribution
3. chain 3: we do not have enough information, the number of iterations is too small



**Figure 11.4:** Diagnostic 1



**Figure 11.5:** Diagnostic 2



**Figure 11.6:** Diagnostic 3

The desired output of MCMC should look like the following plots:

Another more analytical approach is **sample split**. If we split the plot in different regions, do they have the same mean? Do we observe consistency? In chain 2 we need longer warm up, in 3 we need more samples.

Differently from gradient methods, here things are a bit more hard to interpret. We know that eventually we will reach oscillations around the global optimum, but we have no guarantee.

Diagnostics are based on the observation of the results, so they might be biased by our belief and they do not provide an easy way to read “certificate” of convergence.

Another approach may be run more MCMC in parallel and see if they all converge to the same distribution. However, it is again not a certificate of convergence to the global optimum.

Last observation: constraints and bounds can be included easily in the proposal distribution or in the likelihood.

## Chapter 12

# Heuristics and the genetic algorithm

“Heuristics is a fancy name for trial-and-error”.

Heuristics mimic natural selection i.e. follow nature inspired procedures. At the growing of computational power, they become feasible ways to solve optimization problems. There are no warranties on the exactness of the solutions, but often times the results are of high quality. In addition, heuristic algorithms are easy to implement, are general and can include *constraints* (even complex ones).

Example: timetable for plane departures. Deciding when a plane lands is not only a function of flight time, we should take into account delays, passengers, luggages, crew, . . . → constraints. In biological problems we can include relationship among variables which should be satisfied, allowing high flexibility.

There are many famous heuristic algorithms:

- simulated annealing: used in physics, match thermal dispersion
- ant colonies: ant are able to solve many problems e.g. supply chain
- covariance matrix adaptation evolution strategy: performs similarly to adaptive MH algorithm

All these methods have something in common: EVOLUTION STRATEGY.

For observing evolution, we require to have a **population** of candidate solutions - not only by this method, e.g. MCMC. We then select candidates according to their **fitness function** (objective function). The changes in the populations occur as results of variations on the current population.

### 12.0.1 The genetic algorithm

The genetic algorithm (GA) is a family of evolutionary strategies, introduced in 1975 by John Holland. It encodes tentative solutions in chromosomal like structures. Evolution occurs as reproductive opportunities for the fittest. External variation is introduced through *mutations*.

#### Fundamental steps

- encoding of the chromosomes
- generation of an initial population
- fitness evaluation
- parents selection

- 
- reproduction (crossover)
  - mutation
  - new population

The process is repeated from the new population to fitness evaluation. We need to understand how to encode our problem and how the selection of the mutation and reproduction are performed.

#### 12.0.1.1 Chromosome encoding

**Chromosome encoding** is performed through bit strings; we have a long entity  $\theta$  (chromosome) divided into sections (genes).

#### 12.0.1.2 Generation of an initial population

Analogously to the starting points of a multi-start:

- Random
- Latin hypercube
- Orthogonal sampling

#### 12.0.1.3 Fitness evaluation

The objective function for the current population could be picked from known functions e.g. sum of squares, likelihood or more general formulations. As long as there is a connection between the fitness number and candidate selection, the function is fine. MCMC was using one candidate at a time at each iteration, while gradient methods were computing the gradient using information from integration. In this case, the size of the population will determine the number of calls.

#### 12.0.1.4 Parent selection

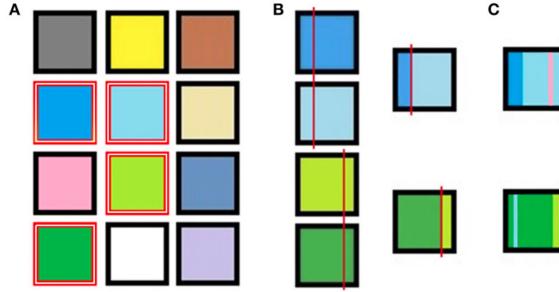
The parents can be selected through:

- threshold based selection - select best k parameters
- random based selection
  - Example (similar to Gillespie, we use fitness instead of the propensity):
    - From  $f^1, \dots, f^N$  compute  $\sum_{i=1}^N f_i = f_0$
    - Generate random number  $j \sim \mathcal{U}(0, 1)$
    - Select the smallest k such that  $\sum_{i=1}^k f_i > j f_0$
    - Clone  $\theta^k$  in an intermediate population

“Roulette selection”, the area of a circle is covered by each chromosome fitness proportionally. The idea is to spin the wheel and select the chromosome where it stops.

#### 12.0.1.5 Reproduction

From the intermediate population we randomly select two individuals  $u, v$  and a gene for cross over  $t$ . We recombine parent chromosomes and add new offspring to the new population. This procedure is only inheriting information from the previous generation, we are missing mutations.



**Figure 12.1:** From Reali et al 2017 - GA procedure example

**Input:** a fitness function  $c$  that measures the goodness of the fit, for example (Equation 5); the population size  $N$ ; the rate of mutation  $\sigma$ ; the maximum number of generations  $G$ .  
**Output:** the best candidate solution  $\tilde{p}$  after  $G$  generations.

```

1 Map the parameters into strings of length  $l$ ;
2 Generate an initial population of strings  $P = \{p_1, \dots, p_N\}$ ;
3 for  $G$  times do
4    $P' = \emptyset$ ;
5   Compute  $f_i = c(p_i)$ ,  $i = 1, \dots, N$  and  $f_0 = \sum_{i=1}^N f_i$ ;
6   for  $N$  times do
7     Generate a random number  $j \sim U(0, 1)$ ;
8     Determine the smallest integer  $k$  such that
9        $\sum_{i=1}^k f_i > jf_0$ ;
10    Update  $P' = p_k \cup P'$ ;
11  end
12  for  $N$  times do
13    Generate two integer random numbers
14     $m, n \sim U(1, N)$ ;
15    Select  $p_m, p_n \in P'$ ;
16    Generate an integer random number  $t \sim U(1, l)$ ;
17     $\tilde{p} = \{p_m[1:t], p_n[t+1:l]\}$ ;
18    for  $i = 1, \dots, l$  do
19      | with probability  $\sigma$  randomly variate  $\tilde{p}[i]$ ;
20    end
21    Update  $P = \tilde{p} \cup P$ ;
22  end
23 Determine the best solution  $\tilde{p}$  such that  $c(\tilde{p}) = \min_{p \in P} c(p)$ ;

```

**Algorithm 3:** A simple Genetic Algorithm.

**Figure 12.2:** From Reali et al 2017 - GA pseudocode

#### 12.0.1.6 Mutation

The offspring may or may not mutate according to a certain probability. We denote  $p$  the probability that a gene of the new offspring mutates.

#### 12.0.2 Genetic algorithm pseudocode

Observations on specifications:

1. how many times do we go? Here we usually start by defining a number of generations
2. size of each population, use function to decide

The cost function is as general as possible. GA is sometimes used for hyperparameters tuning e.g. we can train a NN inside the algorithm. This is not feasible with Markov Chains or gradient methods.

However, we do not know whether the new generation is better than the previous one.

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### **12.0.2.1 Cons**

It is quite computationally demanding, as for  $N$  times we compute the likelihood/cost/fitness just for selecting new parents. Next, we are not directly getting direction, the reduction of the fitness function is not driven by the dimension of the population. Close to the optimum it converges slowly.

### **12.0.2.2 Pros**

Each one of the computations can be parallelized. Some might argue that it can be used for everything. It is very general and obtains good results.  $f$  can vary sometimes; the algorithm can use an obj function without the constraints, that can be added as penalties after some generations.