#### 1 Introduction

There are two fundamental approaches to the mathematical modelling of chemical reactions and diffusion. Deterministic models which are based on differential equations and stochastic models. Stochastic models can be simulated and can keep track of chemical species with low abundances during a reaction.

This report deals with stochastic modelling of reaction diffusion processes.

Every section includes:

- (i) underlying reaction with a brief description
- (ii)relevant algorithm
- (iii)results
- (iv)MATLAB program

## 2 Stochastic Simulation of Degradation

$$A \to \phi$$
 (1)

(i) The reactant A decays with a rate constant k.  $\phi$  represents a chemical species we do not include in our model.

k dt = probability that a randomly chosen molecule of A undergoes reaction in a time interval of [t, t + dt). Given A(t) = number of A molecules at time t A(t) dt = gives the probability that exactly one reaction occurs in a time interval of [t, t + dt).

- (ii) Given that  $A(0) = n_o$ , the algorithm computes A(t) at any time t > 0. Algorithm:
- 1. A random number r uniformly distributed in the interval (0,1) is generated such that the probability that r is the subinterval  $(a,b) \subset (0,1)$  is equal to b-a for any  $a,b \in (0,1), a < b$ .

2.If r < A(t)kdt then A(t+dt) = A(t) - 1 otherwise A(t+dt) = A(t).

Step 1 is repeated and the algorithm is run several times in a loop to obtain the time evolution of number of A molecules and to observe its fluctuations. Since r is a random number uniformly generated from the (0,1) interval the probability that r < A(t)kdt is

the (0,1) interval the probability that r < A(t)kdt is equal to A(t)kdt. Hence step 2 of the algorithm says that the probability that the chemical reaction occurs in the time interval (t+dt) is equal to A(t)kdt.

(iii)

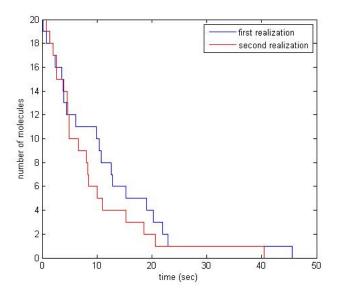


Figure 1: Two realizations of Step 1-2 for  $k=0.1sec^{-1}$  and A(0)=20 with  $\mathrm{d}t=0.005sec$ 

(iv)

```
%% section 2.1
   %a1-b1
   a = 2.0:
   k=0.1;
5
   ds=0.005;
   s=0;
   store_a=zeros(10^5,1);
   for i=1:10<sup>5</sup>
        r=rand(1,1);
                                  %generates ...
10
            random number - Step 1
                                   %checks for the ...
           r < a*k*ds
            probability of reaction occurring -
            Step2
            a = a - 1;
12
                                   %executes the ...
                 reaction - Step 2
            store_a(i,1) = a;
                                  % stores the ...
13
                 changes in number of A ...
                 molecules if any
14
            store_a(i,1) = a;
15
16
        s=s+ds;
17
        store_a(i,2)=s;
19
   end
   stairs(store_a(:,2), store_a(:,1), 'r')
20
```

## 3 Stochastic Simulation of degradation with $\tau$

(i) In the above simulation, when  $r > A(t)k\mathrm{d}t$  there is no change in the number of molecules of A because of which we observe many time intervals in Figure 1 wherein number of molecules remain same. Hence we end up generating many random numbers even though many a times the reaction doesn't occur. In order to reduce the computational intensity we compute  $\tau$  such that from any time t,  $t+\tau$  gives the time at which the next reaction occurs.

Deriving  $\tau$ :

Let f(A(t), s)ds = the probability that next reaction occurs at during the time interval [t + s, t + s + ds), given that A(t) molecules exist at t.

g(A(t),s) = probability that no reaction occurs in [t,t+s).

So, probability that reaction occurs only during the interval ds but not in [t, t + s) is equal to

$$f(A(t), s)ds = g(A(t), s)A(t+s)kds$$
 (2)

Since no reaction occurs in [t, t + s), A(t + s) = A(t). Implying

$$f(A(t), s)ds = g(A(t), s)A(t)kds$$
(3)

To compute probability g(A(t), s) considering  $\rho > 0$  and calculating the probability that no reaction occurs in the interval $[t, t + \rho + d\rho)$  = probability of no reaction in  $[t, t + \rho)*$  probability of no reaction in  $[t + \rho, t + \rho + d\rho)$ . Hence,

$$g(A(t), \rho + d\rho) = g(A(t), \rho)[1 - A(t+\rho)kd\rho] \tag{4}$$

Since no reaction occurs in the interval  $[t,t+\rho), A(t+\rho) = A(t) \\ (g(A(t),\rho+\mathrm{d}\rho) - g(A(t),\rho)/\mathrm{d}\rho = -A(t+\rho)k\mathrm{d}\rho \\ \text{If } \mathrm{d}\rho \to 0, \\ \mathrm{d}g(A(t),\rho)/\mathrm{d}\rho = -A(t+\rho)k\mathrm{d}\rho \\ \text{Solving for the above equation with } g(A(t),0) = 1, \\ g(A(t),\rho) = e^{-A(t)k\rho} \\ \text{Substituting into } 3$ 

$$f(A(t), ds) = A(t)ke^{-A(t)ks}ds$$
 (5)

To find a  $\tau$  such that  $t + \tau$  is time when next reaction occurs, F(.) is defined by  $F(\tau) = e^{-A(t)k\tau}$ .

If  $\tau$  is a random number belonging to the interval  $(0, \infty)$ , then  $F(\tau)$  is uniformly distributed between the interval (0, 1).

Given  $F(\tau)\epsilon(0,1)$ , a uniformly distributed random number r is generated by the algorithm such that  $r = F(\tau)$ .

From 5

$$\tau = 1/(A(t)k)ln[1/r] \tag{6}$$

- (ii) The algorithm slightly modified from the previous section in that now we increment time such that  $t=t+\tau$  wherein  $\tau$  analogous to dt determines the interval after which the next reaction occurs. Algorithm:
- 1. A random number r is generated uniformly distributed in the interval (0,1).
- 2. Compute time of next reaction  $t + \tau$ .
- 3. At  $t+\tau$  change the number of molecules such that  $A(t+\tau)=A(t)-1.$

Steps 1-3 is repeated and the algorithm is run several times in a loop to obtain the time evolution of number of A molecules as done is previous section as well.

(iii)

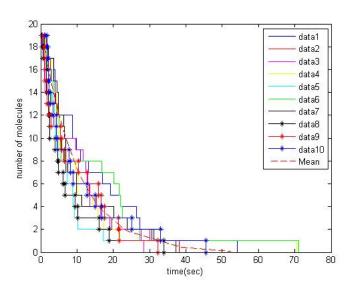


Figure 2: Ten realizations of Step 1-2 for  $k=0.1sec^-1$  and A(0)=20

It is seen that no two realizations for a stochastic simulation are the same. The stochastic mean of A(t) over many realizations is plotted as the dashed curve and was computed using the chemical master equation. The chemical master equation is given by:

$$dp_n/dt = k(n+1)p_{n+1} - knp_n \tag{7}$$

The differential equation can be solved for a solution the mean of which is given by:

$$\sum_{n=0}^{n_o} n p_n(t) = n_o e^{-kt}$$
 (8)

The mean in 8 is also the solution of the deterministic equation given by da/dt = -ka with initial condition of  $a(0) = n_o$ . (iv)

```
a = a -1;
10
                                       % carrying ...
            out the reaction
        if a ==0
11
            t = t + tau;
            store_a(i,2) = t;
14
            break
        end
15
        store_a(i,1) = a;
16
17
        store_a(i,2) = t;
19
   figure(2):
20
   stairs(store_a(1:20,2), store_a(1:20,1), 'b*-')
^{21}
   plot(store_a(1:49,2), store_a(1:49,1),'*')
22
   % mean by master equation
   a = 20;
24
25
   n=\exp(-k.*store_a(1:20,2));
26
   m=a.*n;
   plot(store_a(1:20,2),m,'r--')
```

# 4 Stochastic simulation of Production and Degradation

$$A \to \phi$$
 (9)

$$\phi \to A$$
 (10)

(i) 9 is similar to 1 representing degradation and 10 represents production of molecule A. The rate constant for the degradation reaction is  $k_1$  and for the production reaction is  $k_2$ . The impact of  $\phi$  on the production of A is incorporated into  $k_2$ .

(ii) Algorithm:

1. Two random numbers  $r_1 and r_2$  are generated uniformly from the interval (0,1).

2.  $\alpha_o = A(t)k_1 + k_2$  is calculated.

3.  $\tau = 1/(A(t)k)ln[1/r]$  is calculated and so is the time for next reaction given by  $t+\tau$ .

4. The number of molecules are accordingly adjusted when  $t=t+\tau$  such that

$$A(t+\tau) = A(t) + 1 if r_2 < k_2/\alpha_o$$
 (11)

$$A(t+\tau) = A(t) - 1 \text{ if } r_2 >= k_2/\alpha_o$$
 (12)

 $\alpha_o$  in Step 2 given the combined probability of 9 occurring given by  $A(t)k_1dt$  and 10 occurring given by  $k_2dt$ . Step 3 from the previous section computes the time of next reaction. Once  $t+\tau$  is computed, the second reaction occurs with a probability of  $r_2 < k_2/\alpha_o$ , and the first reaction occurs with (1 - probability of the second reaction). This is given in Step 4 of the algorithm.

To compute the stochastic mean and stochastic fluctuation, the chemical master equation as given in the previous section was constructed for the system of equations. The mean from the master equation for the given system of equations is computed to be the solution of  $dM/dt = -k_1M + k_2$ . Wherein M is the mean and its solution is given by M(t) with an initial condition of M(0) = 0. The solution is plotted as the dashed curve in Figure 3.

The Stochastic mean can be thought as the steady state value of A(t) as  $t \to \infty$ . In order to quantify the fluctuations, either the standard deviation can be calculated or a quantity called the stationary distribution is computed. Stationary distribution is given by :

$$\phi(n) = \lim_{t \to \infty} p_n(t)n = 0, 1, 2, 3, \dots$$
 (13)

The stationary distribution gives the probability that A(t) = n after an infinitely long time. It can be either obtained from a long time simulation or by  $\phi(n) = e^-k2/k1/n!(k2/k1)^n$  obtained from the chemical master equation at the steady state. The results are plotted in Figure 4. The histogram was obtained by running Step 1-4 over  $10^5$  sec and the black line from the equation of  $\phi(n)$ .

(iii)

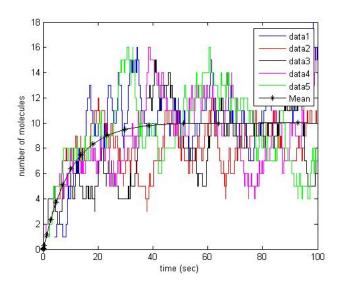


Figure 3: Five realizations of Step 1-4 for  $k_1 = 0.1sec^{-1}$ ,  $k_2 = 1sec^{-1}$  and A(0) = 0

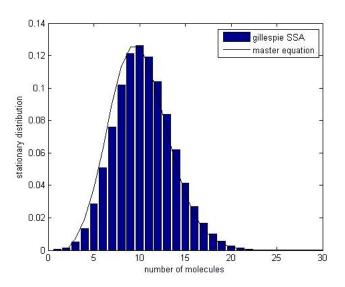


Figure 4: Stationary distribution  $\phi(n)$  obtained by long time simulation (gillespie) and from chemical master equation for  $k_1 = 0.1 sec^{-1}$ ,  $k_2 = 1 sec^{-1}$  and A(0) = 0

(iv)

```
% a3-d3
   for x = 1:5
        a=0;
        k1=0.1;
        k2=1;
        t=0;
        for i =1:10^5
             r1=rand(1.1):
             r2=rand(1,1);
alpha=a*k1 + k2;
10
             tau=(1/alpha) *reallog(1/r1);
11
             if r2 \ge (k2/alpha) % happens only ...
13
                 at t=t + tau
                 a = a -1;
14
             else
15
                 a = a + 1;
             end
17
18
             t=t + tau;
             store_a(i,x)=a;
19
20
             store_t(i,x)=t;
22
        end
   end
23
24
25
   figure(3);
   stairs(store_t(:,1),store_a(:,1))
27
28
   hold on
   stairs(store_t(:,2), store_a(:,2), 'r')
29
   hold on
30
```

```
stairs(store_t(:,3), store_a(:,3),'k')
31
   hold on
32
   stairs(store_t(:,4), store_a(:,4), 'm')
33
   stairs(store_t(:,5), store_a(:,5), 'g')
35
36
   %mean plot
   [T,Y] = ode23(@ode,[0 10000],0);
37
   hold on
38
   plot(T,Y,'k*-')
39
40
   % histogram
41
   max(store_a(:,1))
42
   hist(store_a(:,1),26)
43
   bar(hist(store_a(:,1),26)./10^5)
44
46
   %stationary distribution
47
    x = [0 \ 1];
    k1=0.1;
48
49
    k2=1;
   for n=3:30
51
   x(n) = (exp(-k2/k1)/factorial(n)) * (k2/k1)^n;
52
   end
   x(1) = [];
53
   x(2) = 0;
54
   y=x./sum(x);
55
56
    figure(4);
57
   plot(y)
58
    %% ode file solving for the mean
59
   function dy = ode(t, y)
60
   dy = zeros(1,1);
61
   k1=0.1;
63
   k2=1:
   dy(1) = -k1*y(1) + k2;
64
```

### 5 Gillespie

$$A + A \to \phi \tag{14}$$

$$A + B \to \phi \tag{15}$$

$$\phi \to A$$
 (16)

$$\phi \to B$$
 (17)

(i) The rate constants for the above series of second order chemical reactions are  $k_1, k_2, k_3 and k_4$  respectively. In order to simulate the number of molecules of A and B at any later time t the following algorithm was performed starting with  $A(0) = n_o, B(0) = m_o$  at time t = 0. The probability of a reaction occurring is defined as propensity of the reaction times dt. The propensity of the first reaction is defined as  $\alpha_1 = A(t)A((t) - 1)k_1$ , for the second reaction as  $\alpha_2 = A(t)B(t)k_2$ , for the third as  $k_3$  and fourth as  $k_4$ . The combined propensity of either of the four reactions happening is given by the summation over the propensity of each reaction.

#### (ii)Algorithm:

- 1. Two uniformly distributed random numbers  $r_1 and r_2$  are generated from (0,1) interval.
- 2. The combined propensity is computed and called  $\alpha_o$ . 3. The time when the next reaction occurs is calculated give by  $\tau$  as in the previous section such that  $\tau = 1/alpha_oln[1/r]$ .
- 4. The number of molecules at  $t + \tau$  are updated such that :

$$\begin{split} A(t+\tau) &= A(t) - 2 \, if \, 0 <= r_2 < alpha_1/\alpha_o \\ A(t+\tau) &= A(t) - 1 \, if \\ alpha_1/\alpha_o <= r_2 < alpha_1 + alpha_2/\alpha_o \\ A(t+\tau) &= A(t) + 1 \, if \\ alpha_1 + alpha_2/\alpha_o <= r_2 < alpha_1 + alpha_2 + alpha_3/\alpha_o \\ A(t+\tau) &= A(t) \, if \\ alpha_1 + alpha_2 + alpha_2 + alpha_3/\alpha_o <= r_2 < 1 \end{split}$$

$$\begin{split} B(t+\tau) &= B(t) \ if \ 0 <= r_2 < alpha_1/\alpha_o \\ B(t+\tau) &= B(t) - 1 \ if \\ alpha_1/\alpha_o <= r_2 < alpha_1 + alpha_2/\alpha_o \\ B(t+\tau) &= B(t) \ if \\ alpha_1 + alpha_2/\alpha_o <= r_2 < alpha_1 + alpha_2 + alpha_3/\alpha_o \\ B(t+\tau) &= B(t) + 1 \ if \\ alpha_1 + alpha_2 + alpha_2 + alpha_3/\alpha_o <= r_2 < 1 \end{split}$$

The stationary distribution is now two dimensional given that there are two chemical species A and B and is given by  $\phi(n,m) = \lim_{t \to \infty} p_{n,m}(t)$ . This is obtained by long time simulation of Step 1-4 of the algorithm as depicted in Figure 5. To obtain the stationary distribution along one of the dimensions, the other dimension can be summed over such that  $\phi(n) = \sum_{m=0}^{\infty} \phi(n,m)$  as plotted in Figure 5.

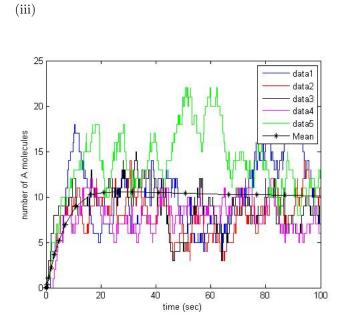


Figure 5: Five realizations with time evolution of number of A molecules with  $A(0) = 0, B(0) = 0, k_1 = 10^-3sec^-1, k_2 = 10^-2sec^-1, k_3 = 1.2^-2sec^-1, k_3 = 1.2sec^-1, k_4 = 1sec^-1$ 

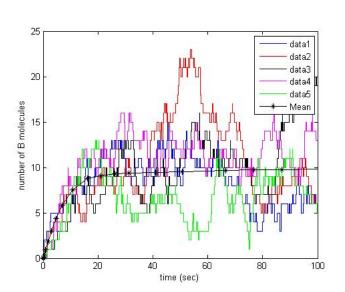


Figure 6: Five realizations with time evolution of number of B molecules with  $A(0) = 0, B(0) = 0, k_1 = 10^-3sec^-1, k_2 = 10^-2sec^-1, k_3 = 1.2^-2sec^-1, k_4 = 1sec^-1$ 

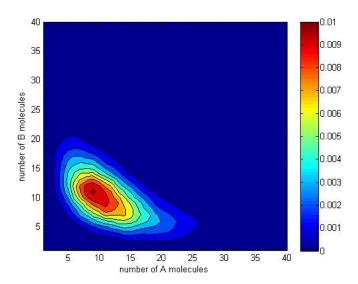


Figure 7: Stationary distribution  $\phi(n,m)$  from long time simulation with  $A(0)=0, B(0)=0, k_1=10^-3sec^-1, k_2=10^-2sec^-1, k_3=1.2^-2sec^-1, k_3=1.2sec^-1, k_4=1sec^-1$ 

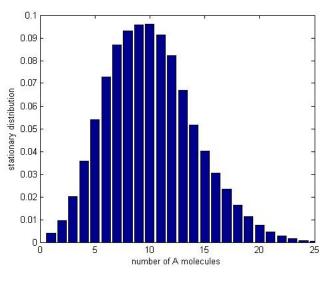


Figure 8: Stationary distribution  $\phi(n)$  with  $A(0) = 0, B(0) = 0, k_1 = 10^-3 sec^-1, k_2 = 10^-2 sec^-1, k_3 = 1.2^-2 sec^-1, k_3 = 1.2 sec^-1, k_4 = 1 sec^-1$ 

```
for z=1:5 %Number of realizations
        a=0;
                  %initialising
        b=0:
3
        k1 = .001;
        k2=0.01;
5
        k3=1.2;
        k4=1;
        t=0;
9
        alpha1=0;
        alpha2=0;
10
        alpha3=0;
11
        alpha4=0;
        alpha=0;
        for i =1:10^6 % number of steps/ runs ...
14
             for each realization
             r=rand(2,1);
15
16
             alpha1=a*(a-1)*k1;
             alpha2=a*b*k2;
17
18
             alpha3=k3;
             alpha4=k4;
19
             alpha=alpha1+alpha2+alpha3+alpha4;
20
                  %Step 2 of algorithm
             tau=(1/alpha)*reallog(1/r(1));
21
                  %Step 3 of algorithm
             mu=r(2)*alpha;
22
                  %Step 4 of algorithm
                mu < alpha1 % happens only at ...
23
                 t=t + tau

a=a-2;
             a- a - 2;
elseif mu < alpha1+alpha2
a= a - 1;
b= b - 1;</pre>
25
26
27
```

```
elseif mu < alpha1+alpha2+alpha3
28
                a = a + 1;
29
30
                 b
                   = b + 1 ;
            end
33
            t=t + tau;
34
            store_a(i,1)=a;
35
36
            store_t(i,1)=t;
            store_b(i,1)=b;
37
38
   end
39
   figure(5);
40
   stairs(store_t(:,1),store_a(:,1))
41
   stairs(store_t(:,2),store_a(:,2),'r')
43
44
   hold on
   stairs(store_t(:,3),store_a(:,3),'k')
45
46
   stairs(store_t(:,4),store_a(:,4),'m')
49
   stairs(store_t(:,5), store_a(:,5), 'g')
50
   figure(6);
51
   stairs(store_t(:,1),store_b(:,1))
52
53
   stairs(store_t(:,2), store_b(:,2), 'r')
55
   hold on
   stairs(store_t(:,3), store_b(:,3), 'k')
56
57
   stairs(store_t(:,4), store_b(:,4), 'm')
58
60
   stairs(store_t(:,5), store_b(:,5), 'g')
61
   %mean
   [T,Y] = ode23(@ode_2,[0 1000],[0 0]);
62
   hold on
63
   plot(T,Y(:,1),'k*-')
   plot(T,Y(:,2),'k*-')
65
66
   %stationary distribution by long time ...
67
        simulation
   z(:,1) = store_a(:,1);
   z(:,2) = store_b(:,1)
69
   stat=zeros(40,40);
70
   for i= 1:length(store_b(:,1))
71
           (((store_a(i,1)>0)&(store_a(i,1)<40))
72
        &((store_b(i,1)>0)&(store_b(i,1)<40)))
73
74
           stat(store_a(i,1),store_b(i,1))=
75
           stat(store_a(i,1), store_b(i,1))+1;
76
77
78
79
   stat=stat./177559;
81
   figure(7)
   contourf(stat)
82
   % histogram
83
84
   %summing over b
86
   \verb|hist(store_a(:,1), max(store_a(:,1))||\\
87
   figure (8)
   bar(hist(store_a(:,1), max(store_a(:,1)))./177559
88
89
   \verb|hist(store_b(:,1), max(store_b(:,1))||
   bar(hist(store_b(:,1), max(store_b(:,1)))./10^8)
91
    if ((A>0)&(A<101))
92
93
           pa(A) = pa(A) + 1;
94
   end:
   pa=pa./10<sup>6</sup>;
   bar(pa);
```

## 6 Smoluchowski equation and diffusion

(i) Diffusion is the random migration of particles or molecules arising from motion due to thermal energy. As a result the trajectory of a particle is not straight and but executes a random walk. The Smoluchowski equations predict the position of the diffusing particle at later time t given its initial position. To do this a random number generator with a zero mean and unit variance and normally distributed is used. Diffusive spreading of the molecule depends on the diffusion constant D which depends on the size of the molecule, absolute temperature and viscosity of the solution. Choosing  $\Delta t = 0.1sec$  starting from [X(0), Y(0), Z(0)] = [0, 0, 0] the algorithm below was

was run for 10mins.

(ii) Algorithm:

1. Three normally distributed random numbers  $r_1, r_2 and r_3$  are generated.

2. The positions of the particle at time  $t+\Delta t$  are computed by

$$X(t + \triangle t) = X(t) + \sqrt{2D\triangle t}r_1$$
  
$$Y(t + \triangle t) = Y(t) + \sqrt{2D\triangle t}r_2$$

 $Z(t + \triangle t) = Z(t) + \sqrt{2D\triangle t}r_3$ 

The X and Y coordinates of the diffusing particle are plotted as in Figure 6.

To obtain the probability distributions, assuming  $\psi(x,y,z)dxdydz$  be the probability that  $X(t)\epsilon[x,x+dx),Y(t)\epsilon[y,y+dy),Z(t)\epsilon[z,z+dz)$  at

time t. Then  $\psi$  evolves according to:  $\frac{\partial \psi}{\partial t} = D \frac{\partial^2 \psi}{\partial x^2} + \frac{\partial^2 \psi}{\partial y^2} + \frac{\partial^2 \psi}{\partial z^2}$ 

Assuming the random walk starting at origin with  $\psi(x,y,z,0)=\delta(x,y,z)$  where  $\delta$  is the Dirac distribution at the origin, the time evolution is  $\psi(x,y,z,t)=\frac{1}{4D\pi t}^{3/2}e^{-\frac{x^2+y^2+z^2}{4Dt}}$ . Figure 6 is probability distribution obtained for two dimensions

obtained by integrating over z, such that

$$\psi(x,y,t) = \frac{1}{4D\pi t} e^{-\frac{x^2 + y^2}{4Dt}}.$$

(iii)

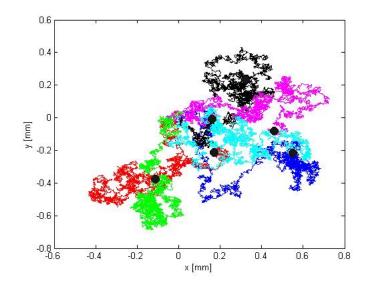


Figure 9: Six trajectories of a random particle for  $D=10^{-4}mm^2sec^{-1}$  and  $\triangle t=0.1sec$ 

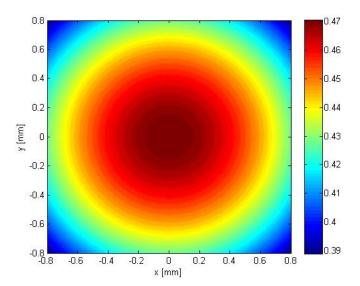


Figure 10: Probability distribution  $\psi(x, y, t)$  given by at t = 10min

```
%a6-b6
   for i = 1: 6 % number of trajectories
        dt = 0.1;
        D=0.0001;
6
        x=0:
        v=0;
7
        z=0;
8
        for n= 1:6000
10
             r=randn(3,1); %updating ...
                  coordinates of the particle
            x = x + (r(1) * sqrt(2*D*dt));
11
            y = y + (r(2) * sqrt(2*D*dt));
12
             z = z + (r(3) * sqrt(2*D*dt));
13
        store_x(n,i)=x;
15
        store_y(n,i)=y;
16
        store_z(n,i)=z;
17
        end
18
19
20
   figure(9);
21
   \verb|plot(store_x(:,1),store_y(:,1)|)|\\
22
   hold on
   plot(store_x(:,2),store_y(:,2),'r')
23
24
   plot(store_x(:,3),store_y(:,3),'k')
   hold on
26
27
   plot(store_x(:,4), store_y(:,4), 'm')
28
   hold on
   plot(store_x(:,5),store_y(:,5),'g')
29
30
   plot(store_x(:,6),store_y(:,6),'c')
31
32
33
   hold on
34
   plot(store_x (end, 1), store_y (end, 1), 'ko'
35
    MarkerSize', 10, 'MarkerFaceColor', [0.1, 0.1, 0.1])
37
   hold on
38
   plot(store_x(end, 2), store_y(end, 2), 'ko'
    MarkerSize',10,'MarkerFaceColor',[0.1,0.1,0.1])
39
40
   plot(store_x (end, 3), store_y (end, 3), 'ko',
  'MarkerSize', 10, 'MarkerFaceColor', [0.1, 0.1, 0.1])
42
43
   hold on
   plot(store_x(end,4),store_y(end,4),'ko',
44
    MarkerSize', 10, 'MarkerFaceColor', [0.1, 0.1, 0.1])
45
46
47
   plot(store_x (end, 5), store_y (end, 5), 'ko',
    'MarkerSize',10,'MarkerFaceColor',[0.1,0.1,0.1])
49
   hold on
   plot(store_x (end, 6), store_y (end, 6), 'ko',
50
     MarkerSize',10,'MarkerFaceColor',[0.1,0.1,0.1])
51
   hold off
53
54
   %prob distribution function in two dimensions
   x=[-0.8:0.01:0.8];
55
   y=[-0.8:0.01:0.8];
56
   for i=1:length(x)
        for j=1:length(y)
59
            prob(i, j) = (1/4*D*6000*pi)*
            \exp(-(x(i)^2+y(j)^2)/4*D*6000);
60
        end
61
62
   figure(10)
   contourf(x,y,prob)
64
65
   shading flat;
```

### 7 Diffusion with boundary

- (i) In the previous section the diffusing molecules is unbounded and free to do a random walk without any boundary restrictions. The algorithm given below has boundary conditions applied demonstrating a reflective boundary condition or a zero flux boundary condition. It is used when there is no chemical interaction between the boundary and the diffusing molecule. Hence choosing  $D=10^{-4}mm^2sec-1, L=1mm, X(0)=0.4mmand\delta t=0.1sec$ , a system of 1000 molecules are released at position x=0.4mm at time t=0.
- (ii) Algorithm: 1.A normally distributed random number  $r_1$  is generated (with zero mean and unit variance).
- 2. The position of the molecule at time  $t + \Delta t$  is computed by  $X(t + \Delta t) = X(t) + \sqrt{2D\Delta t}r_1$ .

3. If  $X(t+\Delta t)$  is less then 0, then  $X(t+\Delta t)=-X(t)-\sqrt{2D\Delta t}r_1~X(t+\Delta t)$  is greater then L, then

$$X(t + \triangle t) = 2L - X(t) - \sqrt{2D\triangle t}r_1$$

The above algorithm is run for  $4minsor\frac{4*60}{\Delta t}steps$ . Ten realizations for a single molecules given the above boundary conditions is shown in Figure 7 . A rather interesting result is the spatial histogram depicting the density of the molecules Figure 7 . This is obtained by simulating 1000 molecules till t=4mins and diving the [0,L] domain into 40 bins of length  $h=L/40=25\mu m$ . The number of molecules in each of the bins is calculated and the distribution is plotted.

(iii)

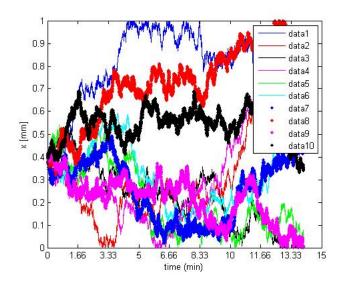


Figure 11: Ten trajectories a random particle with boundary conditions such that  $D=10^{-4}mm^2sec-1, L=1mm, X(0)=0.4mm$  and  $\triangle t=0.1sec$ 

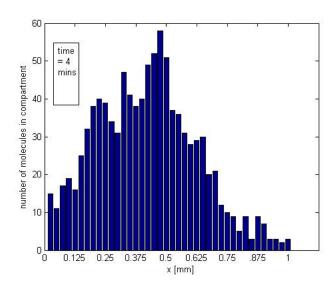


Figure 12: Number of molecules in bins of length  $h=25\mu m$  at t=4min

```
1 %a7-b7
2
3 for i = 1: 1000 % number of molecules
4         D=0.0001;
5         L=1;
6         dt=0.1;
7         x=0.4;
8         for n= 1:2400 % % run for 4 mins
9         r=randn(1,1);
```

```
10
                     (r*sqrt(2*D*dt));
                                             %adding ...
11
                 boundary conditions in the if loop
            x = -x - \frac{1}{2} elseif x > L
                           (r*sqrt(2*D*dt));
                 x= 2*L -x - (r*sqrt(2*D*dt));
14
15
            store_x(n,i)=x;
16
17
19
   end
   figure(11);
20
   plot(store_x(:,1))
^{21}
   hold on
22
   plot(store_x(:,2),
   plot(store_x(:,3),
24
25
   plot(store_x(:,4),
   plot(store_x(:,5),
26
27
   plot(store_x(:,6),
   plot(store_x(:,7),
   plot(store_x(:,8),
30
   plot(store_x(:,9),
   plot(store_x(:,10),'k.')
31
   hold off
32
   Xplot(:,1) = store_x (2400,:);
33
   figure(12);
   h=hist(Xplot(:,1),40);
   bar(h)
```

#### 8 Compartment based approach to diffusion

(i) Instead of simulating 1000 molecules between x = 0 and 1mm and dividing them into 40compartments of  $0.025\mu m$  length each, the time evolution of 40 compartments is carried out directly in this section. This is done by dividing the [0, L] domain into 40 bins and assigning number of molecules to each compartment. Subsequently the time evolution is carried out using the gillespie algorithm using rate constant  $d = D/h^2$ .

Hence the series of reactions between compartments looks as follows:

$$\begin{array}{l} A_1 \leftrightarrow A_2 \leftrightarrow A_3 \leftrightarrow .... \leftrightarrow A_k \\ \text{such that } i=1,2,3,4,...k \ and \ k=40 \ \text{and} \ A_i \leftrightarrow A_{i+1} \\ \text{means that} \ A_i \rightarrow A_{i+1} \ \text{and} \ A_{i+1} \rightarrow Ai. \end{array}$$

#### (ii) Algorithm:

Starting with initial condition  $A_i(t) = a_{o,i}$ . 1. Two random numbers uniformly distributed in (0,1) are

2. The propensity functions of each of the reactions is computed including the forward and backward reactions such that  $\alpha_i = A_i(t)d$  and the combined

propensity is then given by 
$$\alpha_o = \sum_{i=1}^{K-1} \alpha_i + \sum_{i=2}^{K} \alpha_i$$
  
3. The time for next reaction  $t + \tau$  is computed as done

in the previous sections.

4. If 
$$r_2 < \sum_{i=1}^{K-1} \frac{\alpha_i}{\alpha_o}$$
, then finding  $j\epsilon 1, 2, 3....K-1$  such that

that 
$$r_2 >= \frac{1}{\alpha_o} \sum_{i=1}^{i=j-1} \alpha_i \text{ and }$$
 
$$r_2 < \frac{1}{\alpha_o} \sum_{i=j}^{i=j} \alpha_i$$

then the number of molecules are computed as:

$$A_j(t+\tau) = A_j(t) - 1 \tag{18}$$

$$A_{j+1}(t+\tau) = A_{j+1}(t) + 1$$

$$A_{i}(t+\tau) = A_{i}(t)$$
(19)
$$A_{i}(t+\tau) = A_{i}(t)$$
(20)

$$A_i(t+\tau) = A_i(t) \tag{20}$$

for 
$$i \neq j, i \neq j+1$$
  
Else if  $r_2 >= \sum_{i=1}^{K-1} \frac{\alpha_i}{\alpha_o}$ , then finding  $j\epsilon 2,3....K$  such that

$$r_2 >= \frac{1}{\alpha_o} \left( \sum_{i=1}^{i=K-1} \alpha_i + \sum_{i=1}^{i=j-1} \alpha_i \right) \text{ and}$$

$$r_2 < \frac{1}{\alpha_o} \left( \sum_{i=1}^{i=K-1} \alpha_i + \sum_{i=2}^{i=j} \alpha_i \right)$$
then the number of molecules are or

en the number of molecules are computed as:

$$A_i(t+\tau) = A_i(t) - 1 \tag{21}$$

$$A_{j}(t+\tau) = A_{j}(t) - 1$$

$$A_{j-1}(t+\tau) == A_{j-1}(t) + 1$$
(22)

$$A_i(t+\tau) = A_i(t) \tag{23}$$

for  $i \neq j, i \neq j-1$ 

In order to obtain a plot similar to Figure 7, the initial conditions is given by

 $A_{16}(0) = 500, A_{17}(0) = 500 \text{ and } A_i(0) = 0 \text{ for }$  $i \neq 16, i \neq 17$  as x = 0.4mm lies at the boundary of the  $16^{th}$  and  $17^{th}$  compartments. Figure 8 gives the distribution of number molecules in each compartment at time t = 4min. Figure 8 is obtained by simulating the time evolution of 1 particle starting with  $A_{16}(0) = 1$ . The time evolution of the particles across the compartments in plotted a distance measure as 1 compartment =  $0.025\mu m$ .

(iii)

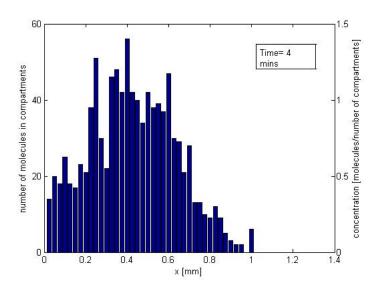


Figure 13: Distribution of molecules in each of the compartments with rate constant  $d = D/h^2$  $0.16sec^{-1}$ , number of compartments K = 40, and  $initial condition A_1 6(0) = 500, A_1 7(0) = 500 and A_i(0) =$  $0 \ for \ i \neq 16, i \neq 17$ 

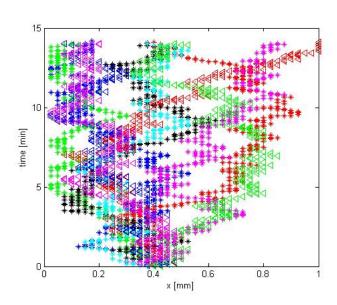


Figure 14: Ten realizations for an individual molecule using the above algorithm

```
%initialisation
       clear;
        clc;
        t=0;
       D=0.0001;
5
       h=0.025; %1/number of compartments
6
        k=D/h^2;
7
       time= 14*60; % corresponds to number ...
        of steps taken by each molecules a = zeros(40,1);
9
       a(16,1)=1;
10
       a(17,1)=0;
11
        alpha_f=zeros(40,1);
12
        alpha_b=zeros(40,1);
13
         n=1;
15
  while t < time
16
17
         %propensities in forward direction
18
         for i=1:39
         alpha_f(i,n) = a(i,n) *k;
20
21
         end
22
         %propensities in backward direction
23
         for i=2:40
25
         alpha_b(i,n) = a(i,n) *k;
26
         end
27
         %computing alpha summation of propensities
28
         alpha = 2*k*1-a(1,n)*k-a(40,n)*k;
29
30
31
         %generating 2 random numbers
         r=rand(2,1);
32
33
         %computing the time of next reaction \dots
34
35
         tau=(1/alpha)*reallog(1/r(1));
36
         %determining which forward reaction occurs
37
         mu=r(2)*alpha;
38
39
41
         a(:,n+1) = a(:,n); %updating molecules ...
         in the next column j=0;
42
         while j < 39
                         % Step 4 of algorithm
43
           if sum(alpha_f(1:j,n)) \le mu
45
                j = j+1;
            else
46
                break
47
            end
48
```

```
49
50
51
         if mu < sum(alpha_f(1:j,n)) %Step 4 of ...
              algorithm
             a(j,n+1)=a(j,n)-1;
53
             a(j+1,n+1)=a(j+1,n)+1;
54
55
57
             forw=sum(alpha_f(:,n)); %Step 5 of ...
                 the algorithm
             z=1:
58
                 while z<40
59
                      if (forw + ...
60
                           \verb"sum" (\verb"alpha-b" (1:z,n)") ) \leq \verb"mu"
61
                          z=z+1;
62
                      else
                          a(z,n+1) = a(z,n)-1;

a(z-1,n+1) = a(z-1,n)+1;
63
64
                          break
                      end
66
                 end
67
68
69
         end
70
         t=t + tau;
71
         store_t(n,1)=t;
72
         n=n+1:
   end
73
74
   %plotting for histogram
75
   figure(13);
   y1=a(:,n);
   x = [1 * 0.025 : 1 * 0.025 : 40 * 0.025];
78
   y2=a(:,n).*0.025;
79
    [hAx] =plotyy(x,y1,x,y2,@bar);
80
   xlabel('x [mm]')
81
   ylabel(hAx(1), 'number of molecules in ...
        compartments') % left y-axis
   vlabel(hAx(2),'concentration ...
83
        [molecules/number of compartments]')
   %plotting 10 realizations
86
   figure(14);
87
   hold on
   a(:,n)=[];
88
   for j=1:n-1
89
        for i=1:40
91
             if a(i,j) == 1
                 plot(i*0.025, store_t(j,1)./60, 'm<')
92
93
                 hold on
            end
94
        end
95
   end
96
```