## A Linear Algorithm for Black Scholes Economic Model

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The pricing of options is a very important problem encountered in financial domain. The famous Black-Scholes model provides explicit closed form solution for the values of certain (European style) call and put options. But for many other options, either there are no closed form solution, or if such closed form solutions exist, the formulas exhibiting them are complicated and difficult to evaluate accurately by conventional methods. The aim of this paper is to study the possibility of obtaining the numerical solution for the Black-Scholes equation in parallel, by means of several processors, using the finite difference method. A comparison between the complexity of the parallel algorithm and the serial one is given.

## **Keywords**: algorithm, model, Black-Scholes, price, evaluation.

## Introduction

Introduction
It is well-known that the Black-Scholes equation is used in computing the value of an option. In sume cases, e.g. a European options, it gives exact solutions, but for other, more complex, numerical attempts are made in order to obtain an approximation of the solution. Several numerical methods are used for solving the Black-Scholes equation.

A European call option is a contract such that the owner may (without obligation) buy some prescribed asset (called the underlying) S at a prescribed time (expiry date) T at a prescribed price (exercice or strike price) K, the risk-free interest rate r (is an idealized interest rate). A European put option is the same as call option, except that "buy" is replaced by "sell".

## 2. Black-Scholes Model for evaluating an option price

Black-Scholes model for a European call option can be described ([7]) or [5] by the following (diffusion-type) partial differential equation (PDE) for this value:

$$\frac{\partial f}{\partial t} + \frac{1}{2}\sigma^2 S^2 \frac{\partial^2 f}{\partial S^2} + rS \frac{\partial f}{\partial S} - rf = 0 \quad (1)$$

with final condition

$$f(S,T) = \max(S - K,0) \tag{2}$$

and boundary conditions

$$f(0,t) = 0, f(S,t) \sim S \quad as \ S \to \infty$$
 (3)

The European put option satisfies the same equation as (2), but with final condition

$$f(S,T) = max(K - S,0)$$
 and boundary conditions (4)

$$f(0,t) = Ke^{-r(T-t)}, f(S,t) \sim 0 \text{ as } S \to \infty$$
 (5)

In both cases, there are explicit closed form solution. For the call option, the solution is

$$f(S,t) = C(S,t) = SN(d_1) - Ke^{-r(T-t)}N(d_2)$$
 (6)

with

$$d_{1} = \frac{\ln \frac{S}{K} + \left(r + \frac{\sigma^{2}}{2}\right)(T - t)}{\sigma\sqrt{T - t}}, \quad d_{2} = d_{1} - \sigma\sqrt{T - t}$$
 (7)

and N(z) is the cumulative distribution function of the standard normal distribution. For the put option,

$$f(S,t) = P(S,t) = Ke^{-r(T-t)}N - (d_2) - SN(-d_1)$$
 (8)

with the same  $d_1$ ,  $d_2$ , and N(z). For most other style option, however, there are no known closed form solution. Thus, approximate method and numerical methods, such as lattice methods ([3], [4]) and finite difference methods ([6]) are used estimate their values.

# 3. Models by using finite difference methods

The finite difference method consists of discretizing the partial differential pricing equation and the boundary conditions using a forward or a backward difference approximation.

We discretize the equation with respect to time and to the underlying asset price. Divide the (S, t) plane into a sufficiently dense grid or mesh, and approximate the infinitesimal steps  $\Delta S$  and  $\Delta t$  by some small fixed finite steps. Further, define an array of N+1 equally spaced grid points  $t_0, t_1, \ldots, t_N$  to discretize the time derivative with  $\Delta t_{n+1} - t_n = \Delta t$  and  $\Delta t = T/N$ .

We know that the stock price cannot go below 0 and we have assumed that  $S_{\rm max}=2S_0$ . We have M+1 equally spaced grid points  $S_0,S_1,\ldots,S_M$  to discretize the stock price derivative with  $S_{m+1}-S_m=\Delta S$  and  $\Delta S=S_{\rm max}/M$ .

This gives us a rectangular region on the (S, t) plane with sides  $(0, S_{\text{max}})$  and (0, T). The grid coordinates (n, m) enables us to compute the solution at discrete points.

The time and stock price points define a grid consisting of a total of  $(M+1)\times(N+1)$  points. The (n,m) point on the grid is the point that corresponds to time  $n\Delta t$  for

 $n = \overline{0, N}$ , and stock price  $m\Delta S$  for  $m = \overline{0, M}$ . We will denote the value of derivative at time step  $t_n$  when the underlying asset has value  $S_m$  as

 $f_{n,m} = f(n\Delta t, m\Delta S) = f(t_n, S_m) = f(t, S)(9)$  where n and m are the number of discrete increments in the time to maturity and stock price respectively. The discrete increments in the time to maturity and the stock price are given by  $\Delta t$  and  $\Delta S$ , respectively.

Let  $f_n = f_{n,0}, f_{n1}, ..., f_{n,M}$  for  $n = \overline{0,N}$ . Then, the quantities  $f_{0,m}$  and  $f_{N,m}$  for  $m = \overline{0,M}$  are referred to as the boundary values which may or may not be known ahead of time but in our PDE they are known. The quantities  $f_{n,m}$  for  $n = \overline{1,(N-1)}$  and  $m = \overline{0,M}$  are referred to as interior points or values.

## 3.1 The Implicit finite difference method.

We express  $f_{n+1,m}$  implicitly in-terms of the unknowns  $f_{n,m-1}$ ,  $f_{n,m}$  and  $f_{n,m+1}$ . We discretize the Black Scholes PDE in (1) using the forward difference for time and central difference for stock price to have:

$$\frac{f_{n+1,m} - f_{n,m}}{\Delta t} + rm\Delta S \left[ \frac{f_{n,m+1} - f_{n,m-1}}{2\Delta S} \right] 
+ \frac{1}{2} \sigma^2 m^2 \Delta S^2 \left[ \frac{f_{n,m+1} - 2f_{n,m} + f_{n,m-1}}{\Delta S^2} \right] = rf_{n+1,m}$$
(10)

Rearranging, we get

$$f_{n+1,m} = \frac{1}{1 - r\Delta t} \left[ \alpha_{1m} f_{n,m-1} + \alpha_{2m} f_{n,m} + \alpha_{3m} f_{n,m+1} \right]$$
 (11)

for  $n = \overline{0, N-1}$  and  $m = \overline{1, M-1}$ . The implicit method is accurate to  $O(\Delta t, \Delta S^2)$ , the parameters  $\alpha_{km}$ 's for k = 1, 2, 3 are given as:

$$\alpha_{1m} = \frac{1}{2} rm\Delta t - \frac{1}{2} \sigma^2 m^2 \Delta t, \quad \alpha_{2m} = 1 + \sigma^2 m^2 \Delta t, \quad \alpha_{3m} = -\frac{1}{2} rm\Delta t - \frac{1}{2} \sigma^2 m^2 \Delta t$$
 (12)

The system of equations can be expressed as a tridiagonal system([1])

$$\begin{bmatrix}
f_{n+1,0} \\
f_{n+1,1} \\
\dots \\
f_{n+1,M-1} \\
f_{n+1,M}
\end{bmatrix} = \begin{bmatrix}
\alpha_{20} & \alpha_{30} & 0 & \dots & 0 & 0 & 0 \\
\alpha_{11} & \alpha_{21} & \alpha_{31} & \dots & 0 & 0 & 0 \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots \\
0 & 0 & 0 & \dots & \alpha_{1M-1} & \alpha_{2M-1} & \alpha_{3M-1} \\
0 & 0 & 0 & \dots & 0 & \alpha_{1M} & \alpha_{2M}
\end{bmatrix} \begin{bmatrix}
f_{n,0} \\
f_{n,1} \\
\dots \\
f_{n,M-1} \\
f_{n,M}
\end{bmatrix}$$
(13)

which can be written as:  $Af_{n,m} = f_{n+1,m}$  for  $m = \overline{0,M}$  (14) Let  $f_n = f_{n,m}$  and  $f_{n+1} = f_{n+1,m}$ , then we need to solve for  $f_n$  given matrix A and column vector  $f_{n+1}$  and this implies that

$$f_n = A^{-1} f_{n+1}$$
 (15)  
We can deduce:

$$f_{n-1} = A^{-1} f_n = (A^{-1})^2 f_{n+1}, \dots, f_0 = (A^{-1})^{n+1} f_{n+1}$$

The matrix 
$$A$$
 has  $\alpha_{2m} = 1 + \sigma^2 m^2 \Delta t > 0, m = \overline{0, M}$ ,

$$\prod_{m=0}^{M} \alpha_{2m} \neq 0$$
, and therefore the matrix is

nonsingular. We can solve the system by finding the inverse matrix  $A^{-1}$ .

When we apply the boundary conditions together with (11), this gives rise to some changes in the elements of matrix A with

$$\begin{cases} \alpha_{20}, \alpha_{2M} = 1 \\ \alpha_{30}, \alpha_{1M} = 0 \end{cases}$$
 (16)

Our initial condition give values for  $N^{th}$  time step, and we solve for  $f_n$  at  $t_n$  in terms

$$\lambda_n = \alpha_{2m} + 2\left[\alpha_{1m}\alpha_{3m}\right]^{1/2}\cos\frac{n\pi}{N} \quad \text{for } n = \overline{1,(N-1)}$$
 (17)

Substituting the values  $\alpha_{1m}$ ,  $\alpha_{2m}$ ,  $\alpha_{3m}$  with values from (14), we have

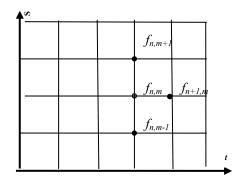
$$\lambda_n = 1 + \sigma^2 m^2 \Delta t + \sigma^2 m^2 \Delta t \left[ 1 - \frac{r^2}{\sigma^4 m^2} \right]^{1/2} \left[ 1 - 2\sin^2\frac{n\pi}{2N} \right] \text{ for } n = \overline{1, (N-1)}$$
 (18)

Furthermore, applying the binomial expansion on the square root part and re-arranging we have

 $\lambda_n \approx 1 + 2\sigma^2 m^2 \Delta t - 2\sigma^2 m^2 \Delta t \sin^2 \frac{n\pi}{2N}$   $\|A\|_2 = \max \left| 1 + 2\sigma^2 m^2 \Delta t - 2\sigma^2 m^2 \Delta t \sin^2 \frac{n\pi}{2N} \right| \le 1$ 

the equation are stable when

of  $f_{n+1}$  at  $t_{n+1}$ . We set the right hand side of the system to our initial condition and solve the system to produce a solution to the equation for time step N-1. By repeatedly iterating in such a manner, we can obtain the value of f at any time step  $0,1,\ldots,N-1$ .



**Fig.1.** Trinomial tree of implicit finite difference discretization

**3.2. The stability of implicit method.** The eigenvalues  $\lambda_n$  are given by

where there is change of sign due to the trun-

cation of the binomial expansion. Therefore

that is,

$$-1 \le 1 + 2\sigma^2 m^2 \Delta t - 2\sigma^2 m^2 \Delta t \sin^2 \frac{n\pi}{2N} \le 1$$
 for  $n = \overline{1, (N-1)}(19)$ 

As 
$$\Delta t \to 0$$
,  $N \to \infty$  and  $\sin^2 \frac{(N-1)\pi}{2N} \to 1$ , 3.3. The results concerning convergence speed of implicit method. For a European

(19) reduces to  $|1| \le 1$ .

Alternatively,  $1 + \sigma^2 m^2 \Delta t \ge 0$  și  $||A||_{\infty} = 1$ 

Therefore by *Lax's equivalence theorem*([2], [6]), the scheme is unconditionally stable, convergent and consistent.

**3.3.** The results concerning convergence speed of implicit method. For a European put option when: S = 20, K = 22, r = 0.1, T = 0.5 şi  $\sigma = 0.25$ , the results content in table **Table 1** shows that when N and M are different, the finite difference methods converges faster than N and M are the same.

**Table** 1. The comparison of the convergence of implicit method for increase N and M

	Implicit			Implicit	<pre>function[P]=impl_method(S,K,r,sigma,T,N,M);</pre>	1
N=M	Method	N	M	Method	dt=T/N;ds=2*S/M;A=sparse(M+1,M+1);	2
10	2.0574	10	20	2,1326	f=max(K-(0:M)*ds,0);// final conditions	3
					for m=1:M-1	4
20	2,1546	20	40	2,2091	x=1/(1-r*dt);	5
30	2.2204	30	60	2,2234	A(m+1,m)=x*(r*m*dt-sigma*sigma*m*m*dt)/2;	6
40	2,2177	40	80	2,2287	A(m+1,m+1)=x*(1+sigma*sigma*m*m*dt);	7
50	2,2286	50	100	2,2328	A(m+1,m+2)=x*(-r*m*dt-sigma*sigma*m*m*dt)/2;	8
60	2,2317	60	120	2,2352	end	9
70	2,2342	70	140	2,2366	A(1,1)=1;A(M+1,M+1)=1;	10
80	2,2352	80	160	2,2377	for i=N:-1:1	11
90	2,2379	90	180	2,2387	$f=A\f'; f=max(f,(K-(0:M)*ds)');$	12
100	2,2374	100	200	2,2393	end	13
				•	P=f(round((M+1)/2));	14

The 11-13<sup>th</sup> lines of program from Table 1 are large consumption of computation time. In practice, there are far more efficient solution techniques than matrix inversion, due to the propriety of A being tridiagonal. Then, methods like LU decomposition or SOR are applied directly to (10), and the execution time is O(N) per solution. In order to compute  $A^{-1}$ , one needs  $(N^2)$  operation and others  $O(M^2)$  to find  $(A^{-1})^m$ , using one processor, so in a serial manner. But with several processors under a convenient network, we show in what follows that we can obtain a time of execution O(N), to compute the inverse  $A^{-1}$ .

# 4. Parallel algorithm for calculating the numerical solution

**4. 1 The Gauss Jordan method for solving a inverse of matrix.** If N = M then A is a  $N \times N$ -square matrix again  $f_n$  and  $f_{n+1}$  are N-dimensional vectors. We use the method of elementary transformation to compute the inverse matrix,  $A^{-1}$  ([6]). In few words, we start from the matrix  $A^1$ , which is obtained from A and a unit matrix, written on the right side of A, as follows:

$$A^{0} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} & 1 & 0 & \cdots & 0 \\ a_{21} & a_{22} & \cdots & a_{2N} & 0 & 1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ a_{N1} & a_{N2} & \cdots & a_{NN} & 0 & 0 & \cdots & 1 \end{pmatrix}$$

**Note**. For the sake of the clearness, we denote by  $a_{i_j}$ ,  $i, j = \overline{1, N}$  all the elements of matrix A, it means  $\alpha_{1m}$ ,  $\alpha_{2m}$ ,  $\alpha_{3m}$  and 0. Fur-

ther, making elementary transformation only on the lines of  $A^0$ , after several steps, we bring it to the form  $A^N$ , where

$$A^{N} = \begin{pmatrix} 1 & 0 & \cdots & 0 & a_{1,N+1} & a_{1,N+2} & \cdots & a_{1,2N} \\ 0 & 1 & \cdots & 0 & a_{2,N+1} & a_{2,N+2} & \cdots & a_{2,2N} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 & a_{N,N+1} & a_{N,N+2} & \cdots & a_{N,2N} \end{pmatrix}$$

The part  $(a_{i,j})_{i=\overline{1,N}, j=\overline{N+1,2N}}$  represents  $A^{-1}$ .

The computation is made in the following manner:

### Step 1.

$$A^{1} = \begin{pmatrix} 1 & a_{12}^{1} & \cdots & a_{1N}^{1} & a_{1,N+1}^{1} & a_{1,N+2}^{1} & \cdots & a_{1,2N}^{1} \\ 0 & a_{22}^{1} & \cdots & a_{2N}^{1} & a_{2,N+1}^{1} & a_{2,N+2}^{1} & \cdots & a_{2,2N}^{1} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & a_{N2}^{1} & \cdots & a_{NN}^{1} & a_{N,N+1}^{1} & a_{N,N+2}^{1} & \cdots & a_{N,2N}^{1} \end{pmatrix}$$

where

$$a_{1j}^{1} = a_{1j} / a_{11}, j = \overline{1,2N}$$

$$a_{ii}^{1} = a_{ii} - a_{1i}^{1} a_{i1}, i = \overline{2,N}, j = \overline{1,2N}$$
(20)

### Step 2.

$$A^{2} = \begin{pmatrix} 1 & 0 & a_{13}^{2} & \cdots & a_{1N}^{2} & a_{1,N+1}^{2} & a_{1,N+2}^{2} & \cdots & a_{1,2N}^{2} \\ 0 & 1 & a_{23}^{2} & \cdots & a_{2N}^{2} & a_{2,N+1}^{2} & a_{2,N+2}^{2} & \cdots & a_{2,2N}^{2} \\ \cdots & \cdots \\ 0 & 0 & a_{N3}^{2} & \cdots & a_{NN}^{2} & a_{N,N+1}^{2} & a_{N,N+2}^{2} & \cdots & a_{N,2N}^{2} \end{pmatrix}$$

where

$$a_{2j}^{2} = a_{2j}^{2} / a_{22}^{2}, \ j = 1,2N$$

$$a_{ij}^{2} = a_{ij}^{1} - a_{2j}^{2} a_{i2}^{1}, \quad i = \overline{1, N, i} \neq 2, \ j = \overline{1,2N}$$
(21)

and so on, till the matrix has the final form

$$egin{pmatrix} 1 & 0 & \cdots & 0 & a_{1,N+1}^N & a_{1,N+2}^N & \cdots & a_{1,2N}^N \ 0 & 1 & \cdots & 0 & a_{2,N+1}^N & a_{2,N+2}^N & \cdots & a_{2,2N}^N \ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \ 0 & 0 & \cdots & 1 & a_{N,N+1}^N & a_{N,N+2}^N & \cdots & a_{N,2N}^N \end{pmatrix}$$

and  $A^{-1}$  is read from the second part of this matrix.

**4.2. Analysis of sequential algorithm.** From (15) and previous section need first decrease the computing time of matrix A. The

number of operations,  $n_{GJ}$ , through Gauss Jordan method is computing remarking a each step s, we calculating N-1 multiplicators. Then([6])

$$n_{GJ} = \sum_{s=1}^{n} \left[ (N-1) + (N-1)(N+1-s) \right] = \frac{N^3}{2} + N^2 - \frac{3N}{2} \approx \frac{N^3}{2} + N^2$$
 (22) function x= for i=2:M+1 gaussjordan(S,K,r,sigma,T,N,M) for j=1:2\*(M+1) 
$$\text{dt=T/N}; \text{ ds=2*S/M}; \text{ A=sparse(M+1,M+1)}; \\ \text{%boundary conditions} \\ \text{A(1,1)=1;A(M+1,M+1)=1}; \\ \text{A(1,2)=0;A(M+1,M)=0}; \\ \text{% tridiagonal matrix form} \\ \text{for pas=2:M+1} \\ \text{for pas=2:M+1} \\ \text{for j=1:2*(M+1)} \\ \text{A(m+1,m)=0.5*r*m*dt-0.5*} \\ \text{D(pas,j)=C(pas,j)/C(pas,pas)};$$

```
sigma*sigma*m*m*dt;
                                          end
  A(m+1,m+1)=(1+sigma*sigma*m*m*dt);
                                          for i=1:M+1
  A(m+1,m+2)=-0.5*r*m*dt-
                                           for j=1:2*(M+1)
            0.5*sigma*sigma*m*m*dt;
                                           if i~=pas
                                           D(i,j)=C(i,j)-D(pas,j)*C(i,pas);
end
B=[A eye(size(A))]; % matrix [A I]
C=B;% Gauss Jordan Algorithm
                                          end
for j=1:2*(M+1)
                                          end
    D(1,j)=C(1,j)/C(1,1);
                                         C=D;
                                         end
end
```

Here an example of execution for M = N = 4:

The initial matrix														
1.0000	0	0	0	0	1.0000	0	0	0	0					
0.0009	1.0025	-0.0034		0	0	1.0000	0	0	0					
0	-0.006	1.0100	-0.0094	0	0	0	1.0000	0	0					
0	0	-0.0047	1.0225	-0.0178	0	0	0	1.0000	0					
0	0	0	0	1.0000	0	0	0	0	1.0000					
	The Ga	uss Jordan	final ma	trix is i	dentical	with Matl	ab call:	inv(A)						
1.0000	The Ga	uss Jordan 0	final ma	trix is i	1.0000	with Matl	ab call:	inv(A)	0					
1.0000	The Ga 0 1.0000	uss Jordan 0	<b>final ma</b> 0 0	trix is i		with Matl 0 0.9975	0 0.0034	0 0.0000	0.0000					
	0	uss Jordan 0 0 1.0000	<b>final ma</b> 0 0	trix is id	1.0000	0	0	0	0 0.0000 0.0002					
	0	0	final ma 0 0 1.0000	0 0 0 0 0	1.0000	0.9975	0.0034	0.0000						

It is clear that, using only one processor to make all computations, the time of execution is  $O(N^3)$ , because we have N steps and every step needs  $O(N^2)$  operations to be computed. In order to reduce the execution time, we can use the parallel calculus.

Having in mind the previous method, we come back to the solving of system (1), using more than one processor. This can be with  $N \times 2N$  processors connected under a lattice

network. In every node of the network there is a processor. According with [1], under this connectivity, every processor  $P_{ij}$  is connected and may transfer information with its four neighbourhood  $P_{i-1,j}$ ,  $P_{i+1,j}$ ,  $P_{i,j-1}$ ,  $P_{i,j+1}$ ,  $i, j = \overline{1, N-1}$ . The computation of the inverse matrix  $A^{-1}$  can be made in the following manner:

Step 0. (Initialization)
$$P_{ij} \leftarrow A^{0}, i = \overline{1, N}, j = \overline{1,2N} \text{ (each processor save } A^{0} \text{ matrix)}$$
Step 1. In parallel do:
$$P_{1j} \leftarrow a_{1j}^{1} = a_{1j} / a_{11}, \quad j = \overline{1,2N}$$

$$P_{ij} \leftarrow a_{ij}^{1} = a_{ij} - a_{1j}^{1} a_{i1}, \quad i = \overline{2, N}, j = \overline{1,2N}$$
Step 2
In parallel do:
$$P_{2j} \leftarrow a_{2j}^{2} = a_{2j}^{1} / a_{22}^{1}, \quad j = \overline{1,2N}$$

$$P_{ij} \leftarrow a_{ij}^{2} = a_{ij}^{1} - a_{2j}^{2} a_{i2}^{1}, \quad i = \overline{1, N}, j = \overline{1,2N}, i \neq 2$$

and so on, till step N, when the matrix in final form is obtained and the inverse matrix  $A^{-1}$  can be read. The effort of computation is of order O(N), because we still have N steps, but in parallel, every step takes the

time for doing a division, a multiplication and a substraction.

**Note.** Due to the fact that at step i, the line of processor  $P_{ij}$ ,  $j = \overline{1,2N}$  executes a division and all the other processors executes a subtraction and a multiplication, the problem of

their synchronization has be taken into account.

**4.3.** Solving the final system in parallel. In the previous paragraph we show how the inverse matrix  $A^{-1}$  can be computed in parallel, with an execution time of order O(N). In order to solve the system (11), which gives

the final numerical solution for the Black-Scholes equation, we have to compute the power m of matrix  $A^{-1}$ . According with [2] and [4], this can be done in a logarithmic time,  $O(\log_2 N)$  using a binary-tree connectivity among processors, like in Figure 2.

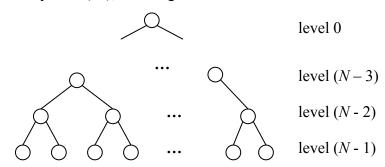


Fig.2. The binary-tree network

**Note.** In every node of this network there is a processor. The idea of computation is the following:

**Step** 1. (Initialization)

Every processor leaf (at level (N-1)) memorizes the matrix  $A^{-1}$ .

**Step** 2. Every processor at level (*N*-2) computes  $(A^{-1})^2 = A^{-1} \cdot A^{-1}$ .

**Step** 3. Every processor at level (*N*-3) computes  $(A^{-1})^4 = (A^{-1})^2 \cdot (A^{-1})^2$  and so on.

After  $\log_2 N$  steps, the final results  $(A^{-1})^N$  will be computed by the processor root.

### 5. Conclusion

We presented an algorithm which generates the numerical solution of the Black-Scholes equation for European option in an execution time of order  $O(N \cdot \log_2 N)$ , using parallel calculus. The binary-tree network can be included in the lattice network, in order to use the same processors.

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