

CHEBYSHEV POLYNOMIAL APPROXIMATION TO APPROXIMATE PARTIAL DIFFERENTIAL EQUATIONS

Guglielmo Maria Caporale
Brunel University and London Metropolitan University

Mario Cerrato
University of Glasgow

March 2008

Abstract

This paper suggests a simple method based on Chebyshev approximation at Chebyshev nodes to approximate partial differential equations. The methodology simply consists in determining the value function by using a set of nodes and basis functions. We provide two examples. Pricing an European option and determining the best policy for chatting down a machinery. The suggested method is flexible, easy to program and efficient. It is also applicable in other fields, providing efficient solutions to complex systems of partial differential equations.

JEL Classification: C63, G12

Keywords: European Options, Chebyshev Polynomial Approximation, Chebyshev Nodes

Corresponding author: Professor Guglielmo Maria Caporale, Brunel Business School, Brunel University, Uxbridge, Middlesex UB8 3PH, UK. Tel.: +44 (0)1895 266713. Fax: +44 (0)1895 269770. Email: Guglielmo-Maria.Caporale@brunel.ac.uk

Acknowledgements: We are grateful to Karim Abadir, Paresh Date, Brian Eales, and Geoff Rodgers for useful comments and suggestions. The usual disclaimer applies.

1. Introduction

The study of partial differential equations (PDE) is a fundamental topic in applied mathematics. In fact, PDEs are fundamental in many applications in physics, natural science and finance. For example, in finance PDEs arise in arbitrage based asset models. The widely cited Black and Scholes PDE, that each European option must satisfy, within an arbitrage free market, it is a canonical example.

In the specific example, (i.e. Black and Scholes model above) the PDE has a specific analytical solution, however, in many other interesting cases in finance as well as other fields, closed form solutions are very difficult to obtain. Therefore, in these cases researchers rely on various numerical methods to obtain a solution. The study of these numerical methods represent the area of Computational Partial Differential Equations.

The most simple applicable algorithm to approximate PDEs rely on the concept of discretisation. That is, replacing the PDE of interest by a finite dimensional problem. However, replacing the PDE by a discrete model is not trivial at all and generally the choice of the finite dimensional model to be used depends on the properties behind the mathematical model itself.

The development of high speed computers has made easier to find accurate solutions to PDEs in a very efficient manner, even in most extreme cases of very large systems of PDEs. In this study we show how using polynomial methods to approximate PDEs. We shall only be focusing on second-order linear PDEs, although it would also be interesting to evaluate this methodology when dealing with non-linear types of PDEs. We leave this on the agenda for future research.

Crack-Nicolson (CN) implicit schemes are amongst the most widely used methods in these cases. However, the effectiveness of the applications of these schemes rely on the choice of the time steps used, and the latter, very often, depend on the problem we are facing. Also CN methods, in general, suffer from poor convergence.

The method suggested in this paper combines polynomial interpolation to approximate the PDE characterising the option pricing problem, and, given our specific applications, we use Monte Carlo method to solve the boundary condition for the PDE.

We fit the functional at Chebyshev nodes to estimate the coefficients¹. The advantage of our approach is its flexibility, and the fact that it is easily implementable and since the functional, at least in the first empirical example, is approximated using deterministic nodes, we obtain less dispersed estimates of the coefficients. In addition, besides our specific applications, our method is applicable in other fields, providing efficient solutions to complex systems of partial differential equations. These features make our approach very attractive. One reason why polynomial approximations of this type are underutilised (in comparison to direct *ad hoc* approximation methods) by applied researchers might be lack of familiarity. Therefore, in Section 3, we provide some guidance on how to use them to solve systems of differential equations.

The layout of the paper is the following. Section 2 describes the option pricing valuation model, which is our application. Section 3 outlines the approximation method we advocate to obtain the solution to the option pricing problem. Section 4 evaluates its empirical performance. Section 5 summarises the main findings of this study and offers some concluding remarks.

¹Tzavalis and Wang (2003) use a similar approach based on Chebyshev approximation to approximate the optimal exercise boundary in the context of a stochastic volatility model. Their method also relies on extrapolation procedures.

2. The Valuation Model

In this paper we present a simple and flexible method to approximate partial differential equations. We start showing how to use the method by pricing an European option. Suppose that the price of a non-dividend-paying asset in period 0 is S_0 , and denote with K the strike price of a put option written on that asset.

Assumption 1: We assume that the option value depends on the stock price at expiry of the option and time, $V_t(S_t, t)$.

Suppose also that the process for S is described by the following geometric Brownian motion:

$$dS_t = S_t r dt + S_t \sigma dZ_t \quad (1)$$

where dZ is a standard increment of a Wiener process, and σ the variance parameter.

We can expand $E(dV) \frac{1}{dt}$, using Ito's Lemma and the stochastic process above to obtain:

$$rV = rSV_s + V_t + \frac{1}{2} S^2 \sigma^2 V_{ss} \quad (2)$$

where $V_{()}$ represents the derivative with respect to the argument in the subscript.

All European options, in absence of arbitrage, must satisfy Equation (2). A call option will have at expiry a payoff given by $S - K$, if $S > K$, while for a put option we have at expiry the payoff $K - S$, if $K > S$. Therefore, in our specific case, the boundary condition is given by

$$V(S, t) = \max(0, K - S) \quad (3)$$

If we set the value function above $V(s, t) \approx \phi(s)c(t)$, where ϕ is a suitable basis for an n -dimensional family of approximating functions and $c(t)$ is an n -vector of time-varying coefficients, equation (2) can be re-written as follows:

$$\phi(s)c'(t) \approx [rs\phi'(s) + \frac{1}{2}\delta^2 s^2 \phi''(s) - r\phi(s)]c(t) \approx \psi(s)c(t) \quad (4)$$

To determine $c(t)$, we select n -values (nodes) of s , s_i , and solve (4) for that particular set of values. Given the n -dimensional family of basis functions chosen, (4) can now be re-written in the form of a system as follows:

$$\Phi c'(t) = \Psi c(t) \quad (5)$$

where Φ and Ψ are two $n \times n$ matrices.

Once the coefficients have been obtained as in (5), to price the financial option, we, first, use the process in (1) to obtain estimates of (3). Finally, we multiply this by the estimated coefficients. Averaging gives the price of the option.

3. Polynomial Approximation

In this section we describe in greater detail the approximation method adopted in this paper. Let $V \in \mathfrak{R}^{n+1}$ be a function defined on the interval $[a, b]$, the latter may well not be tractable analytically, and assume that P is a polynomial that interpolates V at the distinct $n+1$ points $s_i \in [a, b]$, with $P(s) = \sum_{i=0}^n c_i \phi_i(s)$. In order to solve the problem in Section 2 by approximation we need to define: (a) the family of basis functions to approximate the function V , (b) the interpolation nodes, s_i . In this section we show that Chebyshev polynomials in conjunction with Chebyshev nodes offer the best solution to our problem.

Theorem 1: if $V \in \mathfrak{R}[a,b]$, then for all $\varepsilon > 0$ there exists a polynomial $P(s)$ such that $\forall s \in [a,b] |V(s) - P(s)| \leq \varepsilon$.

Remark 1. The above theorem is known as the Weierstrass theorem. It states that any continuous function can be approximated with a certain degree of accuracy by using a polynomial. Although very important theoretically, this theorem is of little practical use since it does not give any indication of what polynomial is the most appropriate to use, or even what order polynomial is needed to achieve a certain degree of accuracy.

The error made by using a polynomial of order n to approximate the function given in Theorem 1 can be easily calculated as:

$$V(s) - P(s) = \frac{1}{n+1} V^{(n+1)}(\xi) \prod_{i=0}^n (s - s_i)$$

The objective of using such an *efficient* polynomial consists in choosing a set of nodes s_i so as to make the term $\prod_{i=0}^n (s - s_i)$ as small as possible (Judd, 1998). One possibility is to approximate the function V at the n -evenly spaced nodes. However, it is well known that in general, even for smooth functions, polynomials of this type do not produce very good approximations.² Therefore, we suggest approximating the function over the interval $[a,b]$, at the Chebyshev nodes defined as:

$$s_i = \cos\left(\frac{2i+1}{2n+2} \pi\right), i = 0, 1, \dots, n$$

Our approach can be justified by appealing to Rivlin's theorem, stating that Chebyshev node polynomial interpolants are nearly optimal polynomial approximants (Rivlin, 1990),

² A classic example is Runge's function (Rivlin, 1990).

and has been shown to perform well empirically (Rivlin, 1990). Chebyshev nodes are also known to possess a further convenient property, i.e. equi-oscillation³(Judd, 1998). As important as the choice of the nodes interpolants is that of a family of functions from which the approximant P will be drawn. We suggest using a Chebyshev polynomial. This is defined as⁴:

$$\Gamma_i(s) = \cos(ia \cos(s)) \quad i = 0, 1, \dots, n$$

with $\Gamma_0(s) = 1$, $\Gamma_1(s) = s$, and $\Gamma_{n+1}(s) = 2s\Gamma_n - \Gamma_{n-1}(s)$

Therefore:

$$V(s) = \sum_{i=0}^n c_i \Gamma_i(s) \quad (6)$$

$$\text{where } c_0 = \frac{1}{n+1} \sum_{i=0}^n V(s_k) \text{ and } c_i = \frac{2}{n+1} \sum_{i=0}^n V(s_k) \cos(ia \cos(s_k)), \quad i = 1, \dots, n$$

A Chebyshev basis polynomial, in conjunction with Chebyshev interpolation nodes, produces an efficient interpolation equation which is very accurate and stable over n . However, in our case, to solve the problem in (3), the polynomial we choose should be able to replicate, not just the function V at s_1, s_2, \dots, s_n , but also its derivatives s'_1, s'_2, \dots, s'_n . Therefore the approximant that solves our problem can be defined as follows⁵:

$$\begin{aligned} \sum_{i=1}^n c_i \Gamma_i(s) &= V(s_i), \forall_i = 1, \dots, n_1 \\ \sum_{i=1}^n c_i \Gamma'_i(s') &= V'(s_i), \forall_i = 1, \dots, n_2 \end{aligned}$$

³ This property states that the maximum error of a cubic function, for example, shall be reached at least five times, and the sign of this error should alternate between the interpolation points.

⁴ Note that in this application we use the general formula for the Chebyshev basis, however there exists also a recursive formula.

⁵ Note that, although one can also use Hermite polynomials to approximate the functional and the slopes, the latter are inefficient (Judd, 1998).

with $n_1 + n_2 = n$.

Once the basis functions (approximants) have been chosen and the approximant nodes defined, the basis coefficients c_i can be obtained. If we define the following Chebyshev-Vandermode type matrix T :

$$T = \begin{bmatrix} \Gamma_0(s_1) & \Gamma_1(s_1) & \dots & \Gamma_{n-1}(s_1) \\ \Gamma_0(s_2) & \Gamma_1(s_2) & \dots & \Gamma_{n-1}(s_2) \\ \dots & \dots & \dots & \dots \\ \Gamma_0(s_n) & \Gamma_1(s_n) & \dots & \Gamma_{n-1}(s_n) \end{bmatrix}$$

then the coefficients c_i ; $c = (c_0, c_1, \dots, c_{n-1})'$ of $V(s)$ solve $Tc = V$, with $\Gamma_{ij} = \Gamma_j(s_i)$ being the j basis function evaluated at the i -th interpolation node. When s is allowed to vary over some other interval, say $[t, T] \neq [-1, 1]$, we rescale the value of s to s^* where

$$s^* = \frac{1}{2}((T-t)s + (T+t))$$
⁶.

As an example of using different basis functions, we anticipate some of the empirical results presented in the next section and after pricing an European option we calculate the approximation error. We use two different basis functions (i.e. Chebyshev basis and spline basis). The approximation error is shown in Figures (1-2).

Insert Figures (1-2) here

As can be seen, when the approximation is calculated using Chebyshev basis functions the error is of the order of 1×10^{-15} for a polynomial of order 20. Spline functions do not

⁶ An interesting issue here is the non-singularity of the Vandermode matrix over Chebyshev basis as above. In theory, there is no guarantee that the matrix is non-singular. However, in practice, in general applications such as ours, we can conjecture that as long as the number of indeterminates exceeds the sparsity with respect to T , non-singularity should hold. Alternatively, we suggest two ways to overcome the problem: (a) simply use the singular value decomposition of T ; (b) use the generalised Vandermode matrix over Chebyshev. In fact, for this type of matrix Werther (1993) proves that, as long as the indeterminates take a value $[1, \infty]$, the generalised Vandermode matrix over Chebyshev basis is non-singular.

achieve a comparable degree of accuracy even increasing the order of the polynomial to 30. Furthermore, Chebyshev polynomials exhibit their usual oscillation which appears fairly evenly over the interval we have considered. On the other hand, spline polynomials exhibit larger oscillations at the edges of the interval.

4. Option Pricing

To show how to empirically use the proposed method we provide now two examples. We start with the first example, which has already described in section 2. In the first case, we use the proposed methodology to value an European put option written on a stock . In this case, there is the possibility to compare the empirical result given by our methodology with the Black and Scholes closed form solution. We use the absolute error (ASE) as a measure of accuracy.

Table 1 shows the results for the entire set of options considered. We also report the results using the Black and Scholes method (1973 - B&S henceforth).

Insert Table 1 here

We fit (4) using the first twenty Chebyshev basis to estimate the parameters c_i in (4)⁷. The basis number has been chosen using Theorem 6.4.2 in Judd (1998). Once the coefficients have been estimated, we estimate the boundary condition in (3) by simulating 200,000 paths for the stock. We can see that regardless the option considered, our method produces rather accurate option prices. The absolute error reported at the bottom of Table 1 confirms that.

⁷ Note that we estimate these coefficients using Chebyshev nodes and Chebyshev basis.

6. Investment Under Uncertainty

The second empirical example we consider is taken from the Investment theory under uncertainty. We consider the case of having to decide when it is optimal to shutdown a machinery, assuming that there is no maintenance cost for maintaining the machine alive. Suppose that $\pi(t)$ is the profit generated by the machinery at time t , and suppose that it follows the Brownian motion process below

$$d\pi(t) = a dt + \sigma dz, \quad \pi(0) = \pi_0 \quad (7)$$

where a is the rate of depreciation of the investment, σ is the volatility of profit, and dz is an increment of a Wiener process.

We report three paths of the process in Figure 3. We have considered the parameters reported at the bottom of Table 3 and the time $T = 10$, has been divided in one-hundred time steps. As it appears clear, the investment will, in general, produce a loss before 3 years. However the decision to shutdown the machinery cannot be only taken by looking at the dynamics of these paths. In fact, this is a more complex problem since once the machinery has been shutdown it cannot be re-started again. That is the investment is irreversible. Therefore, one has to consider the optimal policy to decide when it is convenient to shutdown the investment.

Following Dixit and Pindyck (1994), suppose that $F(\pi, t)$ is a claim of the profit flow, π , and suppose it is determined as

$$F(\pi, t) = \max_{\tau \in \Gamma} E \int_0^T e^{-rt} \pi(t) dt \quad (8)$$

where r is the risk free rate of interest, T is the time and $\tau \in \Gamma$ is a random stopping time.

Suppose that the machinery can be eliminated only up to time \bar{T} . After that time it has to run forever. We assume that if the machinery is eliminated cannot be re-installed, this assumption highlights the irreversibility of the investment.

The Bellman Equation for the optimal stopping problem can be written as

$$F(\pi, t) = \max(0, \pi dt + (1 - rdt)^{-1} E[F(\pi + d\pi, t + dt)]) \quad (9)$$

Therefore, if the machinery is eliminated the profit will be zero. If we continue to hold alive the machinery, then the profit is given by the conditional expectation in (9). One can show that for this case, the value function F , in the continuation region, satisfies the following Bellman equation

$$rF = \pi + aF_{\pi} + 1/2\sigma^2 F_{\pi\pi} \quad (10)$$

where F_{π} is the derivative with respect to the sub-script.

Under the assumption that if not abandoned by \bar{T} , the machinery has to run forever, the terminal condition can be written as $F(\pi, \bar{T}) = \max(0, a/r^2 + r/\pi)$.

We can still use the same approach as in Section (3) to solve this optimal stopping problem. However, now solving (10) at each stopping times require more effort. One way could consist in using finite difference methods. However, this approach turns out to be very time consuming. On the other hand using Richardson extrapolation methods would increase the speed but at a cost of, sometimes, poor convergence. The method described in Section (3) can be adapted to this specific case. In fact, it is very similar in spirit to the

Least-Squares algorithm introduced in Longstaff and Schwartz (2001). The coefficient c in Section 3 are still estimated using Chebyshev polynomials and the same approach as before but now the interpolant nodes are projected using (7)⁸. We assume that there is a threshold at \$0.87 and once it has been reached one has to decide if it is convenient to shutdown the machinery. Using 200 time steps, four Chebyshev basis functions and one hundred thousands replications, we estimate that it is optimal to shutdown the machinery soon after its second year of life. This empirical result is in line with the three paths shown in Figure (3).

⁸ We have also tried to estimate the parameters using Chebyshev nodes but in this specific case we obtained a poor fit. Therefore we suggest, when dealing with optimal stopping problems, to not use Chebyshev nodes.

7. Conclusions

In this study we suggest a simple way to approximate partial differential equations suggesting a method based on Chebyshev approximation at Chebyshev nodes. We provide two empirical examples. The first example consisted in pricing an European put option. The second example consisted in solving an optimal stopping problem. In the last example the proposed methodology did not use deterministic nodes to approximate the functional but rather stochastic ones. Our method is simple to apply and extend and provide a reliable framework which can be applied either to price more complex derivative instruments or used in many interesting cases in economics. We leave this on the agenda for future research.

References

Abadir, K., and M., Rockinger, 2003, “Density Functionals, With An Option-Pricing Application”, *Econometric Theory*, 4.

Barone-Adesi, G., and R.E. Whaley, 1987, “Efficient Analytic Approximation of American Option Values”, *Journal of Finance*, 42, 301-320.

Black, F. and M. Scholes, 1973, “The Pricing of Options and Corporate Liabilities”, *Journal of Political Economy*, 81, 637-654.

Breen, R., 1991, “The Accelerate Binomial Option Pricing Model”, *Journal of Financial and Quantitative Analysis*, 26, pp. 53-164.

Chang, C., C.S. Chung and R.C. Stapleton, 2002, “Richardson Extrapolation Techniques for the Pricing of American-Style Options”, Department of Finance, The Management School, National Central University, Taiwan, Working Paper No. 3.

Cox, J.C., S.A. Ross and M. Rubinstein, 1979, “Option Pricing: A simplified Approach”, *Journal of Financial Economics*, 7 229-263.

Dixit, A., 1992, “Investment and Hysteresis”, *Journal of Economic Perspectives*, 6, 107-132.

Dixit, A., and S. Pindyck, 1994, “Investment Under Uncertainty”, Princeton University Press.

Geske, R. and H. Johnson, 1984, “The American Put Option Valued Analytically”, *Journal of Finance*, 39, 1511-1524.

Ju, N., and R. Zhong, 1999, “An Approximate Formula For Pricing American Options”, *Journal of Derivatives*, 7, 31-40.

Judd, K., 1998, “Numerical Methods in Economics”, Massachusetts Institute of Technology Press.

Longstaff, F.A. and E.S. Schwartz, 2001, “Valuing American Options by Simulation: A Simple Least-Squares Approach”, *Review of Financial Studies*, 14, 1, 113-147.

Moreno, M., and J., Novas, 2001, “On the Robustness of Least Squares Monte Carlo for Pricing American Derivatives”, Universitat Pompeu Fabra, Department of Economics and Business, working papers in Finance N.o 2.

Pindyck, R.S., 1991, “Irreversibility and the Explanation of the Investment Behaviour”, in D. Lund and B., Oksendal (eds.), *Stochastic Models and Option Values*, Amsterdam, North Holland.

Rivlin, Theodore J., 1990, “Chebyshev Polynomials: From Approximation Theory to Algebra and Number Theory”, 2nd edition, New York: John Wiley and Sons.

Stentoft, L., 2003, “Assessing the Least Squares Monte Carlo Approach to American Option Valuation”, University of Aarhus, School of Economics & Management, working papers in finance N.o 10.

Sullivan, A.M., 2000, “Valuing American Put Options Using Gaussian Quadrature”, *Review of Financial Studies*, 1, 75-94.

Tzavalis, E., and S. Wang, 2003, “Pricing American Options Under Stochastic Volatility: A New Method Using Chebyshev Polynomials to Approximate the Early Exercise Boundary”, Working Paper No. 488, Queen Mary, University of London, Department of Economics.

Werther, T., 1993, “Generalized Vandermode Determinants over the Chebyshev Basis”, International Computer Science Institute, 1947, Center Street, Berkeley, California.

Tables and Figures

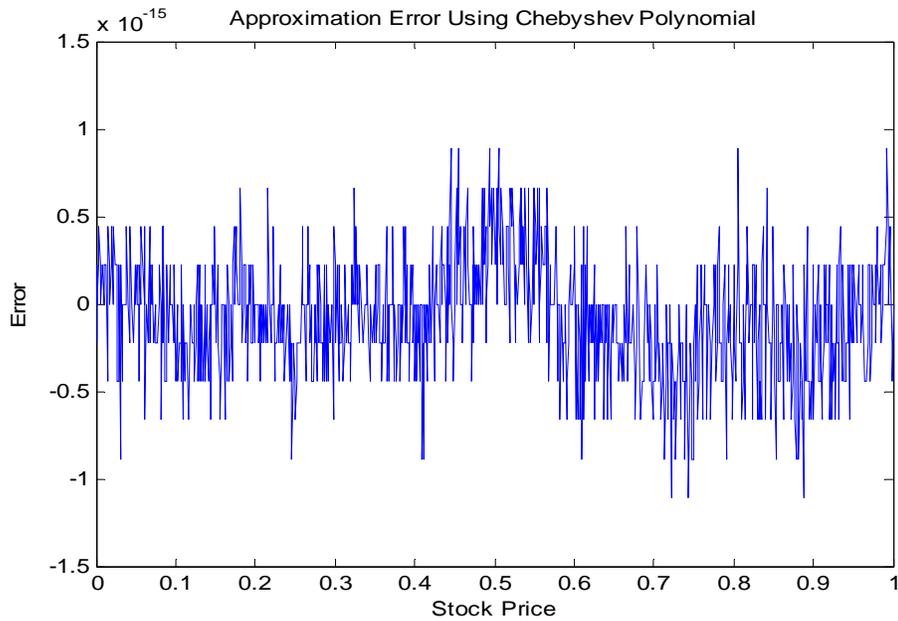


Figure 1

Approximation error using (8) and Chebyshev polynomial when volatility is equal to 0.2 and the interest rate is 0.048.

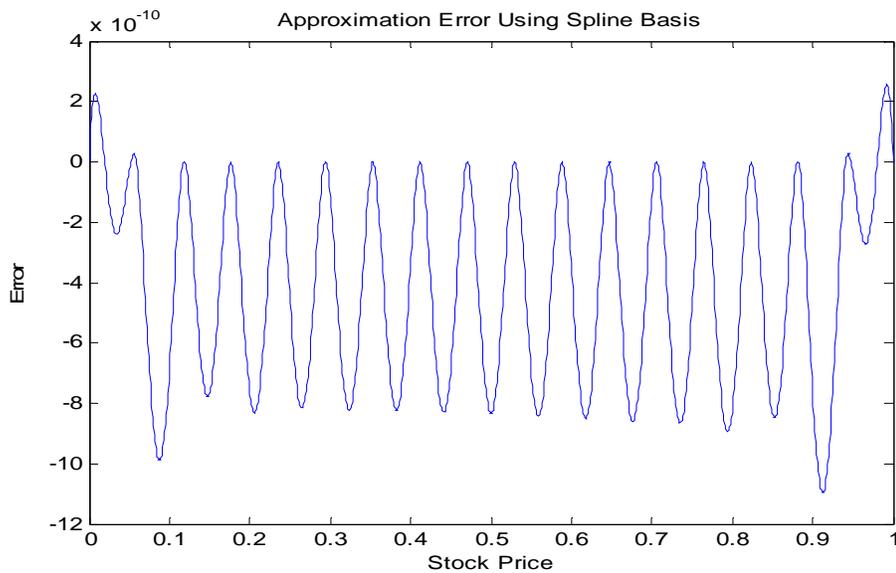


Figure 2

Approximation error using (8) and splines basis when volatility is equal to 0.2 and the interest rate is 0.048

K	Sigma	t (yrs)	B&S	CC (2008)
40	0.2	0.0833	0.8403	0.838
40	0.2	0.3333	1.5221	1.472
40	0.2	0.5833	1.8812	1.802
45	0.2	0.0833	4.8399	4.837
45	0.2	0.3333	4.7804	4.771
45	0.2	0.5833	4.84	4.813
40	0.3	0.0833	1.2988	1.297
40	0.3	0.3333	2.4275	2.426
40	0.3	0.5833	3.0634	3.062
45	0.3	0.0833	4.9796	4.976
45	0.3	0.3333	5.5288	5.517
45	0.3	0.5833	5.9723	5.946
40	0.4	0.0833	1.7575	1.758
40	0.4	0.3333	3.3336	3.3335
40	0.4	0.5833	4.2473	4.246
45	0.4	0.0833	5.236	5.235
45	0.4	0.3333	6.3767	6.359
45	0.4	0.5833	7.1654	7.131
ABE				0.0151

Table 1

Column 4 shows the results using the Black and Scholes (1973) method.

Column 5 shows the results using our suggested method (Caporale and Cerrato – CC).

RMSE at the bottom of the table is the root mean square error.

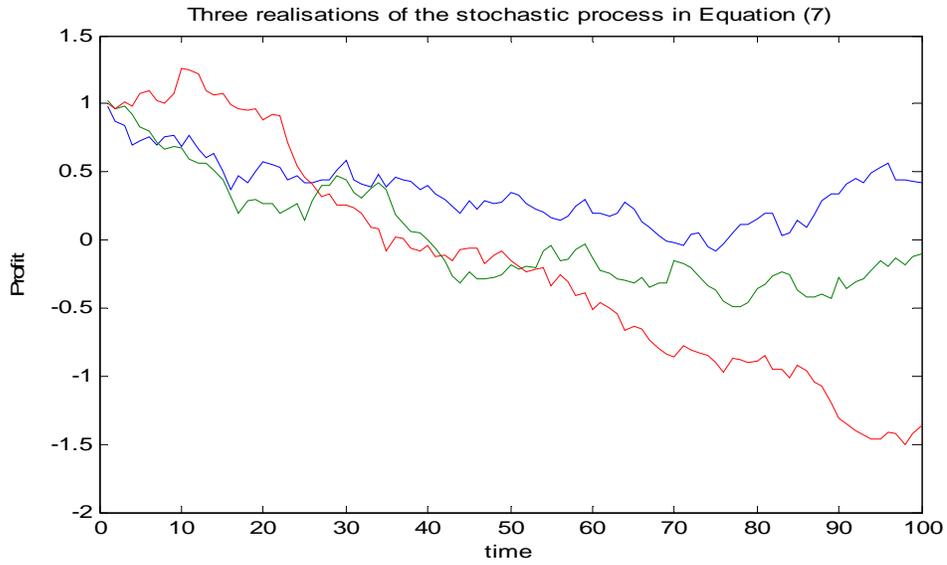


Figure 3

The stochastic process in Figure 3 has been simulated using $a = -0.1$, $\sigma = 0.2$, and $\pi_0 = 1$.