Randomized quasi Monte Carlo methods for pricing of barrier options under fractional Brownian motion

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Abstract. Randomized quasi-Monte Carlo (RQMC) method is presented to compute the problem of a barrier option pricing. It is assumed that stock prices are modeled with a fractional Brownian motion (FBM). The FBM is a Gaussian process with dependent and stationary increments except $H = \frac{1}{2}$. The FBM can model stock prices with short or long memory. We propose a trajectory generation technique based on fast Fourier transforms to simulate stock prices modeled by FBM. A stock price trajectory is utilized to predict pricing of barrier options. Barrier options are options whose payoff function depends on the stock prices during the option's lifetime. Using the results of the stock price trajectory and RQMC method can be determined the price of a barrier option under FBM. We conclude that RQMC is an efficient technique for calculating the price of barrier options rather than a standard Monte Carlo (MC).

1. Introduction

Monte Carlo (MC) method is one way that can overcome financial problems, especially in determining option prices. MC method is a method that uses random numbers to determine an expected value of a random variable. These random numbers are pseudo-random numbers (PRN) that have a certain probability distribution. However, this method has a slow speed of convergence and rather time-consuming, because a root of the average decay error is $O(N^{-1/2})$, where $N$ is a number of samples.

Quasi-Monte Carlo (QMC) method is an efficient alternative to the standard MC method, which is able to achieve faster convergence and higher accuracy [1,2]. The QMC method is based on using a low-discrepancy sequence (LDS), also called a quasi-random number for sampling point. LDS is designed so that the integration domain resembles a uniform distribution but the process of determining random numbers is deterministic. However, PRN is a random number that has a uniform distribution and fulfills statistical properties.

With deterministic QMC method, it is difficult to estimate integration errors in practice. Randomized quasi-Monte Carlo (RQMC) method is used to replace QMC method. RQMC method combines LDS and PRN. In this paper, Halton and Sobol sequence, which are LDS with a different deterministic model, will be applied in RQMC method for calculating a barrier option pricing.

Analytical formulas for calculating barrier options are not available in many cases such as barrier options under the FBM model and options with many assets. The MC method is one that plays an
important role in this situation. The MC algorithm is an algorithm based on simulating several stock price trajectories under a risk-neutral probability measure. A price of barrier options with the MC method has been discussed at [3–6]. Meanwhile, the price of barrier options under the FBM model using RQMC method has never been discussed. The purpose of this paper is to determine the price of a barrier option using RQMC method.

2. Fractional Brownian motion
An FBM $B^H_t = \left( B^H_t \right)_{t \geq 0}$ is a Gaussian process with a zero mean and a covariance function is defined

$$E[B^H_tB^H_u] = \frac{1}{2}\left( |t|^{2H} - |t-u|^{2H} + |u|^{2H} \right),$$ (1)

where Hurst index $H \in (0, 1)$ and $t, u \geq 0$, see [7]. More precisely, by using (1), we obtain that covariance between $X_s = B^H_t - B^H_u$ and $X_{s-u} = B^H_{t-u} - B^H_{s-u}$ is

$$\rho_H(u) = \frac{1}{2}\left( (u-1)^{2H} - 2u^{2H} + (u+1)^{2H} \right).$$ (2)

A FBM coincides with a standard BM if $H = \frac{1}{2}$. The Hurst index $H$ determines the sign of the covariance of the future and past increments. This covariance is negative when $H \in \left(0, \frac{1}{2}\right)$, positive when $H \in \left(\frac{1}{2}, 1\right)$, and zero when $H = \frac{1}{2}$. As a consequence, it has short-range dependence (short memory) for $H \in \left(0, \frac{1}{2}\right)$ and it has long-range dependence (long memory) for $H \in \left(\frac{1}{2}, 1\right)$.

The stock price model under the FBM is given by

$$dS_t = \mu S_t dt + \sigma S_t d\hat{B}^H_t, \quad t \in [0, T], S_0 > 0,$$ (3)

where $\mu$ and $\sigma$ are constants, $\hat{B}^H_t$ is the FBM with respect to $\hat{P}^H$. The fractional Black-Scholes model consists of one riskless asset (bank account) and one risk asset (stock). The stock price satisfies a stochastic differential equation (3). By using a change of variable $\sigma \hat{B}^H_t = \sigma B^H_t - \mu + r$ and using the Girsanov theorem in [7], we have

$$dS_t = rS_t dt + \sigma S_t dB^H_t, \quad t \in [0, T], S_0 > 0.$$ (4)

Furthermore, we obtain a solution of (4) as

$$S_t = S_0 \exp\left( rt + \sigma B^H_t - \frac{1}{2} \sigma^2 t^{2H} \right),$$ (5)

by using an Itô formula in [7].

3. Pricing of barrier options
Path-dependent options are options whose behavior on stock prices during its lifetime. Unlike vanilla options, the price of path-dependent options depends not only on a stock price at maturity but also on stock prices trajectory during the contract. There are many types of path-dependent options, such as Asian options, lookback options, and barrier options. Each option has unique characteristics. Path-dependent options offer premium prices that are cheaper than the standard vanilla option.

A barrier option is a option that can be activated or deactivated if the stock price reaches a certain price level ($L$). Barrier options in general consist of two types, namely knock in and knock out options. A knock out option is an option whose contract is canceled if the stock price crosses the barrier value. A knock in option, on the other hand, is activated if the stock price crosses the barrier value. The relationship between a barrier value $L$ and a current stock price $S_0$ indicates whether the option is an up or down option. We have an up option if $L > S_0$ and we have a down option if $L < S_0$. Combining the payoffs of call and put options with these features, we can define an array of barrier options.
An option is said to be an up-and-out option if the stock price crosses a barrier value and the value is greater than the current stock price. A down-and-out option is an option which the stock price crosses a barrier value and the value is below the current stock price. The payoff of an up-and-out call option with barrier value \( L \), expiration time \( T \) and strike price \( K \), is given by
\[
f(S_T) = (S_T - K)^+ \mathbf{1}_{\sup \{S_s \leq L\}}
\]
and the payoff of a down-and-out call option is given by
\[
f(S_T) = (S_T - K)^+ \mathbf{1}_{\sup \{S_s \geq L\}}
\]
The payoff function of a put option is defined similarly with \( (K - S_p)^+ \) in place of \( (S_T - K)^+ \).

A closed form formula for an option barrier pricing under a fractional Brownian motion model has not been found. This is because a fractional Brownian motion no longer has markovian and martingale properties so the reflective principle used to derive formulas for barrier options is no longer valid. So it is difficult to get an analytical solution from the barrier option pricing.

4. Randomized quasi Monte Carlo
Option pricing using the MC method can be determined in the following three stages
- Simulate sample trajectories from stock prices during a time interval \([0, T]\) as many as \( m \) times,
- Calculate a discounted expected value of a payoff function of a barrier option for each trajectory that generated in the first stage,
- Average the value that calculated in the second stage.

In the vanilla option, there is actually no need to make a stock price trajectory, only the stock price at maturity is of concern. Barrier options are options that depend on the trajectory of a stock prices. The barrier option pricing is determined by whether the stock price passes a certain barrier value during the option period. Because of this path-dependent, all stock price simulations are needed during the option period. To simulate a sample trajectory, we must choose a stochastic differential equation that illustrates price dynamics. Stochastic equations for a stock price under FBM are written in (5).

QMC simulation is based on the same procedure as MC simulation but uses LDS instead of PRN. Similar to PRN, LDS is algorithmically generated by a computer, except that the LDS is determined deterministically in a smart way to be more uniformly distributed than PRN. In contrast to an MC sample, LDS do not have the independent and identically distributed (i.i.d.) property.

Therefore, we cannot directly use LDS in the QMC method. However, randomized LDS samples can be constructed by changing LDS into the following form
\[
\hat{U}_i = (U_i + W_i) \mod 1,
\]
where \( W_i \) is a PRN and \( U_i \) is an LDS. The vector \( \hat{U}_i \) is uniformly distributed in the unit hypercube and sequence \( \hat{U} \) have the independent and identically distributed property. Thus, the estimators based on \( \hat{U}_i \) are unbiased.

The best known quasi-random number generations [8] are Halton sequences, Faure sequences, Sobol sequences, and the lattice method. This paper only discusses two quasi-random number generations, namely Sobol sequences and Halton sequences. Sobol sequences are examples of LDS. Ilya M Sobol, a Russian mathematician, first introduced Sobol sequences [9] in 1967. Sobol points can be produced using algorithms introduced by Bratley and Fox [10]. Halton Sequences are sequences that produce points in space using numerical methods such as appear to be random. The Halton sequence was first introduced in 1964 [11] and developed by Kocis and Whiten [12].

5. Numerical Results
In this section, we first simulate sample trajectories from stock prices at time intervals \([0, T]\). The stock price is modeled using equation (5). The algorithm for building trajectories of stock prices using quasi random numbers is seen in Algorithm 1. Using the algorithm can be generated trajectories of
stock prices like Figure 1. Figure 1 also says that when $H = 1/2$, the FBM will be the same as the standard BM.

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Algorithm 1. Stock price trajectories under FBM
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\begin{algorithm}
\caption{Algorithm 1. Stock price trajectories under FBM}
\begin{algorithmic}
\State \textbf{Input}: Set an expire date $T$, an initial stock price $S_0$, an interest rest $r$, a stock volatility $\sigma$, a Hurst index $H$ and a large number $n$ of equally spaced subintervals in $(0, T)$
\State \textbf{output}: $S_t$ with $t = t_1, t_2, \ldots, t_n \in [0, T)$
\State \textbf{Set using pseudo random number, Halton sequences or Sobol sequences;}
\For{$j \leftarrow 1$ \textbf{to} $n$}
\State Generate two pseudo-random number $W_{1j}$ and $W_{2j}$;
\If{pseudo random number}
\State $U_{1j} \leftarrow W_{1j}$ and $U_{2j} \leftarrow W_{2j}$;
\Else
\State Generate two two Halton or Sobol sequences $U_{1j}$ and $U_{1j}$;
\State $\tilde{U}_{1j} \leftarrow (U_{1j} + W_{1j}) \mod 1$ and $\tilde{U}_{2j} \leftarrow (U_{2j} + W_{2j}) \mod 1$;
\EndIf
\State RandomComplex $\leftarrow \tilde{U}_{1j} + \tilde{U}_{2j}$;
\EndFor
\State $\rho(1) = 1$;
\For{$k \leftarrow 1$ \textbf{to} $n$}
\State $\rho_{k+1} \leftarrow \frac{1}{2} \left((k-1)^{2H} - 2k^{2H} + (k+1)^{2H}\right)$;
\EndFor
\State $\rho_{\text{new}} \leftarrow [\rho; \rho(\text{end} - 1 : -1 : 2)]$
\State $\lambda \leftarrow \frac{\text{Real}(\text{FFT}(\rho_{\text{new}}))}{n}$
\State $X \leftarrow \text{FFT}\left(\sqrt{\lambda}\right) \ast \text{RandomComplex}$
\State $W \leftarrow \text{CUMSUM}(\text{Real}(X(1 : n + 1)))$
\For{$j \leftarrow 1$ \textbf{to} $n$}
\State $S_{t_j} \leftarrow S_0 \exp\left(rT - \frac{1}{2} \sigma^2 \left(\frac{X_j}{n}\right)^{2H} + \sigma \left(\frac{T}{n}\right)^H W_j\right)$
\EndFor
\end{algorithmic}
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Figure 1. Stock price trajectories under FBM by using Sobol sequences
If $H < \frac{1}{2}$ the trajectory of the stock price fluctuates greatly, and if $H > \frac{1}{2}$ the trajectory of the stock price is more likely to be smooth.

Algorithm 2 is an algorithm used to calculate the pricing of a barrier option under an FBM model using MC and RQMC. The pricing of a barrier option can be determined using the trajectory of stock prices generated in Algorithm 1. The pricing of a barrier option generated in Algorithm 2 is an up-and-out call option. Other barrier options can be calculated by changing lines 4-6 in Algorithm 2 according to the payoff function of the option. All algorithms in this paper are written and executed in the Matlab program.

**Algorithm 2.** Price of an up-and-out call option using randomized quasi Monte Carlo

We present an example to show the effectiveness of Algorithm 2. We use current stock price $S_0 = 500$, strike price $K = 500$, expiration date $T = 1$, stock volatility $\sigma = 0.05$, index Hurst $H = 0.8$, and interest rate $r = 0.05$. We implement the MC and RQMC simulation algorithms and compare the results obtained from all methods. The RQMCS method is the RQMC method while the LDS used is the Sobol sequence. Whereas, the RQMCH method is the RQMC method by using the Halton sequence.

| $M$ | $N$ | Price of an up-and-out call option | Error of an option price |
|-----|-----|------------------------------------|--------------------------|
|     |     | MC | RQMCS | RQMCH | MC | RQMCS | RQMCH |
| 100 | 1000| 17,24898 | 14.07713 | 13.99044 | 1.52361 | 0.94219 | 1.01528 |
| 1000| 1000| 14.49144 | 14.97568 | 15.00420 | 0.47331 | 0.32219 | 0.32139 |
| 10000| 1000| 15.09796 | 15.23683 | 15.15125 | 0.15128 | 0.10101 | 0.10141 |
| 100000| 1000| 15.27597 | 15.29528 | 15.23070 | 0.04809 | 0.03201 | 0.03199 |

Table 1 is the pricing of an up-and-out call option with the MC and RQMC methods using the Sobol and Halton sequences based on a large number of subintervals, $N = 1000$, and sample sizes, $M = 100, 1000, 10000$ and 100000. Using the results in Table 1, we can conclude that the RGMC method is more efficient than the MC method. Whereas in Table 2 it compares three methods with large numbers of subintervals, $N = 100, 1000, 10000$ and 100000, and sample sizes, $M = 1000$. In this table also concludes the same thing, the RQMC method is more efficient.

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Table 2. Price of an up-and-out call option with $N = 10^2$, $10^3$, $10^4$, $10^6$

| M   | N   | Price of an up-and-out call option | Error of an option price |
|-----|-----|------------------------------------|--------------------------|
|     |     | MC       | RQMCS  | RQMCH  | MC       | RQMCS  | RQMCH  |
| 1000| 100 | 14,38474 | 14,97417 | 15,97086 | 0,47787  | 0,32375 | 0,31689 |
| 1000| 1000| 15,20676 | 14,74686 | 15,41580 | 0,48841  | 0,32536 | 0,32023 |
| 1000| 10000| 15,53449 | 14,98866 | 14,44457 | 0,48684  | 0,31704 | 0,31358 |
| 1000| 100000| 15,13752 | 15,30209 | 15,23531 | 0,47789  | 0,32155 | 0,32103 |

6. Conclusion
One of the methods to determine the pricing of a barrier option under an FBM model is to use the RQMC methods. The stock price trajectory under the FBM model has been proposed in Algorithm 1. Using Algorithm 1 can be determined the barrier option price under the FBM model with the MC and RQMC methods described in Algorithm 2. We compare the accuracy of MC and RQMC method in the pricing of barrier option under the FBM model. The RQMC method more efficient than the MC method which is shown by smaller errors.

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References
[1] Jäckel P 2002 *Monte Carlo Methods in Finance* (Wiley)
[2] Glasserman P 2003 *Monte Carlo methods in financial engineering* (Springer Science & Business Media)
[3] Moon K S 2008 Efficient Monte Carlo algorithm for pricing barrier options *Commun. Korean Math. Soc.* 23 285–94
[4] Shevchenko P V. and Del Moral P 2014 Valuation of Barrier Options using Sequential Monte Carlo 1–30
[5] Alzubaidi H 2016 Efficient Monte Carlo algorithm using antithetic variate and brownian bridge techniques for pricing the barrier options with rebate payments *J. Math. Stat.* 12
[6] Nouri K and Abbasi B 2017 Implementation of the modified Monte Carlo simulation for evaluate the barrier option prices *J. Taibah Univ. Sci.* 11 233–40
[7] Biagini F, Hu Y, Öksendal B and Zhang T 2008 *Stochastic Calculus for Fractional Brownian Motion and Applications* (Springer)
[8] Kroese D P, Taimre T and Botv Z I 2011 *Handbook of Monte Carlo Methods* (Wiley Series in Probability and Statistics)
[9] Sobol’ I M 1967 On the distribution of points in a cube and the approximate evaluation of integrals *Zhurnal Vychislitel’noi Mat. i Mat. Fiz.* 7 784–802
[10] Bratley P and Fox B L 1988 ALGORITHM 659: implementing Sobol’s quasirandom sequence generator *ACM Trans. Math. Softw.* 14 88–100
[11] Halton J H 1964 Algorithm 247: Radical-inverse quasi-random point sequence *Commun. ACM* 7 701–2
[12] Kocis L and Whiten W J 1997 Computational Investigations of Low- Discrepancy Sequences *ACM Trans. Math. Softw.* 23 266–94