

The copyright © of this thesis belongs to its rightful author and/or other copyright owner. Copies can be accessed and downloaded for non-commercial or learning purposes without any charge and permission. The thesis cannot be reproduced or quoted as a whole without the permission from its rightful owner. No alteration or changes in format is allowed without permission from its rightful owner.



**MODELING FINANCIAL ENVIRONMENTS USING  
GEOMETRIC FRACTIONAL BROWNIAN MOTION MODEL  
WITH LONG MEMORY STOCHASTIC VOLATILITY**

**MOHAMMED KAMEL ALHAGYAN**



**DOCTOR OF PHILOSOPHY  
UNIVERSITI UTARA MALAYSIA  
2018**



Awang Had Salleh  
Graduate School  
of Arts And Sciences

Universiti Utara Malaysia

**PERAKUAN KERJA TESIS / DISERTASI**  
(*Certification of thesis / dissertation*)

Kami, yang bertandatangan, memperakukan bahawa  
(*We, the undersigned, certify that*)

**MOHAMMED KAMEL MOHAMMED AL HAQYAN**

calon untuk Ijazah \_\_\_\_\_ PhD  
(*candidate for the degree of*)

telah mengemukakan tesis / disertasi yang bertajuk:  
(*has presented his/her thesis / dissertation of the following title*):

**"MODELING FINANCIAL ENVIRONMENTS USING GEOMETRIC FRACTIONAL BROWNIAN MOTION MODEL WITH LONG MEMORY STOCHASTIC VOLATILITY"**

seperti yang tercatat di muka surat tajuk dan kulit tesis / disertasi.  
(*as it appears on the title page and front cover of the thesis / dissertation*).

Bahawa tesis/disertasi tersebut boleh diterima dari segi bentuk serta kandungan dan meliputi bidang ilmu dengan memuaskan, sebagaimana yang ditunjukkan oleh calon dalam ujian lisan yang diadakan pada : **24 Januari 2018**.

*That the said thesis/dissertation is acceptable in form and content and displays a satisfactory knowledge of the field of study as demonstrated by the candidate through an oral examination held on:  
January 24, 2018.*

Pengerusi Viva:  
(*Chairman for VIVA*)

Assoc. Prof. Dr. Maznah Mat Kasim

Tandatangan  
(Signature)

Pemeriksa Luar:  
(*External Examiner*)

Assoc. Prof. Dr. Maheran Mohd Jaffar

Tandatangan  
(Signature)

Pemeriksa Dalam:  
(*Internal Examiner*)

Dr. Teh Raihana Nazirah Roslan

Tandatangan  
(Signature)

Nama Penyelia/Penyelia-penyalia:  
(*Name of Supervisor/Supervisors*)

Tandatangan  
(Signature)

Nama Penyelia/Penyelia-penyalia:  
(*Name of Supervisor/Supervisors*)

Tandatangan  
(Signature)

Tarikh:

(Date) January 24, 2018

## **Permission to Use**

In presenting this thesis in fulfilment of the requirements for a postgraduate degree from Universiti Utara Malaysia, I agree that the Universiti Library may make it freely available for inspection. I further agree that permission for the copying of this thesis in any manner, in whole or in part, for scholarly purpose may be granted by my supervisor(s) or, in their absence, by the Dean of Awang Had Salleh Graduate School of Arts and Sciences. It is understood that any copying or publication or use of this thesis or parts thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to Universiti Utara Malaysia for any scholarly use which may be made of any material from my thesis.

Requests for permission to copy or to make other use of materials in this thesis, in whole or in part, should be addressed to:

Dean of Awang Had Salleh Graduate School of Arts and Sciences

UUM College of Arts and Sciences

Universiti Utara Malaysia

06010 UUM Sintok

## Abstrak

Model Pergerakan Pecahan Geometrik Brownian (GFBM) digunakan dengan meluas dalam persekitaran kewangan. Model ini mengandungi parameter penting iaitu min, ruapan, dan indeks Hurst, yang bererti kepada kebanyakan masalah dalam bidang kewangan terutamanya bagi menentukan harga opsyen, nilai pada risiko, kadar tukaran, dan insuran cagaran. Kebanyakan penyelidikan terkini mengkaji *GFBM* dengan mengandaikan ruapannya adalah malar disebabkan keringkasannya. Walau bagaimanapun, anggapan ini selalunya disangkal dalam kebanyakan kajian empirikal. Oleh itu, kajian ini membangunkan model GFBM baharu yang mampu menerangkan dan menggambarkan situasi sebenar dengan lebih baik terutamanya dalam senario kewangan. Kesemua parameter yang terlibat dalam model yang dibangunkan dianggar menggunakan algoritma inovasi. Kajian simulasi seterusnya dilakukan untuk menentukan prestasi model baharu. Hasil simulasi mendedahkan bahawa penganggar yang disyorkan adalah cekap berdasarkan kepada kepincangan, varians, dan min kuasa dua ralat. Seterusnya, dua teorem berkaitan kewujudan dan keunikan penyelesaian bagi model baharu dan pengitlakannya dibina. Pengesahan bagi model yang dibangunkan kemudiannya dilakukan dengan membandingkannya dengan beberapa model lain bagi meramal harga terlaras Standard and Poor's 500, Shanghai Stock Exchange Composite Index, dan FTSE Kuala Lumpur Composite Index. Kajian empirikal terhadap empat aplikasi kewangan terpilih, iaitu penentuan harga opsyen, nilai risiko, kadar pertukaran, dan insuran gadai janji, menunjukkan bahawa model baharu mempamerkan keputusan yang lebih baik berbanding model sedia ada. Justeru itu, model baharu amat berpotensi untuk dijadikan model pendasar bagi sebarang aplikasi kewangan yang berupaya mencerminkan keadaan sebenar dengan lebih tepat.

Universiti Utara Malaysia

**Kata kunci:** Pergerakan Pecahan Geometrik Brownian, ruapan stokastik, memori panjang, senario kewangan.

## Abstract

Geometric Fractional Brownian Motion (GFBM) model is widely used in financial environments. This model consists of important parameters i.e. mean, volatility, and Hurst index, which are significant to many problems in finance particularly option pricing, value at risk, exchange rate, and mortgage insurance. Most current works investigated GFBM under the assumption of its volatility that is constant due to its simplicity. However, such assumption is normally rejected in most empirical studies. Therefore, this research develops a new GFBM model that can better describe and reflect real life situations particularly in financial scenario. All parameters involved in the developed model are estimated by using innovation algorithm. A simulation study is then conducted to determine the performance of the new model. The results of simulation reveal that the proposed estimators are efficient based on the bias, variance, and mean square error. Subsequently, two theorems on existence and uniqueness of the solution for the new model and its generalisation are constructed. The validation of the developed model was then carried out by comparing with other models in forecasting adjusted prices of Standard and Poor 500, Shanghai Stock Exchange Composite Index, and FTSE Kuala Lumpur Composite Index. Empirical studies on four selected financial applications, i.e. option pricing, value at risk, exchange rate, and mortgage insurance, indicate that the new model performs better than the existing ones. Hence, the new model has strong potential to be employed as an underlying model for any financial applications that capable of reflecting the real situation more accurately.

**Keywords:** Geometric Fractional Brownian Motion, stochastic volatility, long memory, financial scenario.

## Acknowledgement

I am grateful to the Almighty Allah for giving me the opportunity to complete my PhD thesis. May peace and blessing of Allah be upon His beloved Prophet Muhammad (SAW), his family, and his companions.

Firstly, I would like to express my sincere gratitude to my advisors Dr. Masnita Misiran and Prof. Dr. Zurni Omar for the continuous support of my Ph.D. study, for their patience, motivation, and immense knowledge. Their guidance helped me in all the time of research and writing of this thesis. I could not have imagined having a better advisors and mentors for my Ph.D. study.

I thank my fellow labmates for good deal, for the stimulating discussions, for the sleepless nights we were working together before deadlines, and for all the fun we have had in the last five years.

I deeply thank my parents, Kamel Alhagyan and Wadha Metlaq for their unconditional trust, timely encouragement, and endless patience. It was their love that raised me up again when I got weary.

I would like to thank my brothers and sisters; Ali, Dyana, Dana, Abrar, Anwar, Lubna and Abd Allah for supporting me spiritually throughout writing this thesis and my life in general.

Last but not least, I thank with love to Suheir, Bashar, Basheer and Ihab, my wife and my sons. Suheir has been my best friend and great companion, loved, supported, encouraged, interested, and helped me get through this agonizing period in the most positive way.

## Table of Contents

Permission to Use.....	i
Abstrak.....	ii
Abstract.....	iii
Acknowledgement.....	iv
Table of Contents.....	v
List of Tables.....	viii
List of Figures.....	x
List of Appendices.....	xiii
List of Abbreviations.....	xiv
<b>CHAPTER ONE: INTRODUCTION .....</b>	<b>1</b>
1.1 Research Background.....	1
1.1.1 Discrete Stochastic Volatility and Continuous Stochastic Volatility.....	4
1.1.2 Long Memory in Financial Modeling.....	5
1.1.3 Geometric Fractional Brownian Motion (GFBM) .....	10
1.2 Problem Statement .....	13
1.3 Research Objective.....	14
1.4 Limitation of the Study .....	15
1.5 Significance of the Research .....	15
1.6 Outline of the Thesis .....	16
<b>CHAPTER TWO: PRELIMINARIES AND LITERATURE REVIEW.....</b>	<b>18</b>
2.1 Preliminaries .....	18
2.2 Stochastic Volatility Models in Financial Environment .....	20
2.3 Stochastic Volatility Models Perturbed by Long Memory .....	27
2.4 Content Analysis on Stochastic Volatility in the Literature .....	39
2.4.1 Jump .....	42
2.4.2 Multivariate Models .....	42
2.4.3 Long Memory Stochastic Volatility.....	43
2.4.4 Simulation Based Inference .....	44
2.4.5 Moment – Based Inference .....	45

<b>CHAPTER THREE: NEW MODEL OF GEOMETRIC FRACTIONAL BROWNIAN MOTION PERTURBED BY LONG MEMORY STOCHASTIC VOLATILITY .....</b>	<b>46</b>
3.1 Development of the Model.....	46
3.1.1 Deriving Geometric Fractional Brownian Motion Covariance.....	46
3.1.2 Estimating Geometric Fractional Brownian Motion Parameters .....	51
3.2 Simulation Study.....	58
3.2.1 Validation of Calculations .....	58
3.2.2 Results of the Simulation Study.....	62
3.2.2.1 Algorithm of Simulation.....	63
3.2.2.2 Numerical Results .....	66
3.3 Discussion .....	80
<b>CHAPTER FOUR: EXISTENCE AND UNIQUENESS SOLUTION OF FRACTIONAL STOCHASTIC DIFFERENTIAL MODEL .....</b>	<b>82</b>
4.1 Preliminaries Definitions and Theorems.....	82
4.2 Existence and Uniqueness Solution of Geometric Fractional Brownian Motion Model .....	85
4.3 Existence and Uniqueness solution of Fractional Stochastic Differential Model	95
4.4 Discussion .....	106
<b>CHAPTER FIVE: VALIDATION OF THE DEVELOPED MODEL BASED ON DIFFERENT TYPES OF MARKET INDICES .....</b>	<b>107</b>
5.1 Characteristic of Market Indices .....	109
5.1.1 Standard and Poor's 500 .....	110
5.1.2 Shanghai Stock Exchange Composite Index .....	110
5.1.3 FTSE Bursa Malaysia KLCI.....	111
5.2 Validation of the Developed Model.....	111
5.2.1 Forecasting the Performance of Standard and Poor's 500.....	112
5.2.1.1 Description of Data.....	112
5.2.1.2 Forecasting Standard and Poor's 500 .....	113
5.2.2 Forecasting the Performance of Shanghai Stock Exchange Composite Index .....	128

5.2.2.1 Description of Data.....	128
5.2.2.2 Forecasting the Shanghai Stock Exchange Composite Index .....	129
5.2.3 Forecasting the Performance Kuala Lumpur Composite Index.....	141
5.2.3.1 Description of Data.....	141
5.2.3.2 Forecasting of Kuala Lumpur Composite Index .....	142
5.3 Discussion .....	156
<b>CHAPTER SIX: APPLICATIONS OF DEVELOPED LONG MEMORY STOCHASTIC VOLATILITY MODEL IN FINANCE .....</b>	<b>158</b>
6.1 Pricing the Options.....	158
6.1.1 Fractional Black–Sholes Model for European Option Pricing .....	159
6.1.2 Description of Data .....	160
6.1.3 Pricing the Options .....	162
6.2 Value at Risk and Long Memory .....	168
6.2.1 Description of Data .....	172
6.2.2 Calculating Value at Risk with Self-similarity .....	174
6.3 Exchange Rate.....	177
6.3.1 Description of Data .....	178
6.3.2 Forecasting Exchange Rates .....	180
6.4 Mortgage Insurance.....	189
6.4.1 Description of Data .....	190
6.4.2 Valuing Insurer Potential Loss.....	192
6.5 Discussion .....	196
<b>CHAPTER SEVEN: CONCLUSIONS AND RECOMMENDATIONS.....</b>	<b>199</b>
7.1 Conclusion .....	199
7.2 Future Research Problems and Recommendations .....	201
<b>REFERENCES.....</b>	<b>202</b>

## List of Tables

Table 1.1	Representation of memory dependence families .....	9
Table 1.2	Models of stochastic processes describing $Y_t$ in SV models .....	11
Table 1.3	Popular SV models .....	12
Table 2.1	Current Stochastic Volatility Models.....	32
Table 2.2	The evolution of stochastic volatility from 2001–2011 .....	40
Table 3.1	Calculation of the proposed method for sample size $n = 1$ .....	59
Table 3.2	Parameters estimates for sample size $n = 1$ .....	59
Table 3.3	Calculation of the proposed method for sample size $n = 2$ .....	60
Table 3.4	Parameters estimates for sample size $n = 2$ .....	60
Table 3.5	Calculation of the proposed method for sample size $n = 3$ .....	61
Table 3.6	Parameters estimates for sample size $n = 3$ .....	62
Table 3.7	Brief summary of the procedure for selected simulation algorithms....	63
Table 3.8	Simulation Based on Simulated Annealing Algorithm.....	69
Table 3.9	Simulation Based on Nelder–Mead Algorithm.....	70
Table 3.10	Simulation Based on Random Search Algorithm .....	71
Table 3.11	Simulation Based on Differential Evolution Algorithm .....	72
Table 3.12	Simulation of mean reverting parameter ( $\alpha$ ) for different sizes and different methods, with best variance, bias, and mean square error in $\{\cdot\}$ , $(\cdot)$ and $[\cdot]$ respectively.....	75
Table 3.13	Simulation of mean of volatility parameter ( $m$ ) for different sizes and different methods, with best variance, bias, and mean square error in $\{\cdot\}$ , $(\cdot)$ and $[\cdot]$ respectively.....	76
Table 3.14	Simulation of volatility of volatility parameter ( $\beta$ ) for different sizes and different methods, with best variance, bias, and mean square error in $\{\cdot\}$ , $(\cdot)$ and $[\cdot]$ respectively.....	77
Table 3.15	Simulation of drift parameter ( $\mu$ ) for different sizes and different methods, with best variance, bias, and mean square error in $\{\cdot\}$ , $(\cdot)$ and $[\cdot]$ respectively.....	78
Table 5.1	Formulas of Volatility .....	108

Table 5.2	The scale of judgment of forecast accuracy using MAPE .....	109
Table 5.3	The values of volatilities according to the formulas of Simple (S), Log (L), High-Low-Close (HLC) and Stochastic (STO).....	114
Table 5.4	Forecasted Prices and Actual Prices of S&P 500 with MAPE .....	115
Table 5.5	The level of accuracy ranking for forecasting model of S&P 500.....	122
Table 5.6	The values of volatilities according to the formulas of Simple (S), Log (L), and Stochastic (STO) .....	129
Table 5.7	Forecasted prices and actual prices of SSE with MAPE .....	131
Table 5.8	The level of accuracy ranking for forecasting model of SSE .....	137
Table 5.9	The values of volatilities according to the formulas of Simple (S), Log (L), High-Low-Close (HLC) and Stochastic (STO).....	142
Table 5.10	Forecasted Prices and Actual Prices of KLCI with MAPE .....	144
Table 5.11	The level of accuracy ranking for forecasting model of KLCI.....	150
Table 6.1	Summary of parameters .....	162
Table 6.2	Comparison of the European call option prices using different methods with $H$ in ( ) and $\sigma^2$ in [ ].....	164
Table 6.3	Parameters summary of PRPFX .....	174
Table 6.4	PRPFX :VaR model with memory and stochastic volatility versus VaR model with no memory and constant volatility .....	175
Table 6.5	Formulas of volatility.....	180
Table 6.6	Volatility values according to different formulas .....	181
Table 6.7	Forecast value for exchange rate USD/MYR with MSE .....	182
Table 6.8	The level of accuracy ranking for forecasting models.....	185
Table 6.9	The models under consideration .....	192
Table 6.10	Involved parameters value .....	193
Table 6.11	Collaterals values and their corresponding potential loss.....	194

## **List of Figures**

Figure 2.1.	Numbers of articles in long memory stochastic, volatility, jumps, moment-based inference, and simulation-based inference. ....	41
Figure 5.1.	Daily adjusted price series of S&P 500 from 1 <sup>st</sup> January 2015 to 31 <sup>st</sup> December 2015.....	112
Figure 5.2.	Daily returns series of S&P 500 from 1 <sup>st</sup> January 2015 to 31 <sup>st</sup> December 2015.....	113
Figure 5.3.	Forecast prices of S&P 500 by using GBM-S and GFBM-S vs actual prices.....	124
Figure 5.4.	Forecast prices of S&P 500 by using GBM-L and GFBM-L vs actual prices.....	125
Figure 5.5.	Forecast prices of S&P 500 by using GBM-HLC and GFBM-HLC vs actual prices .....	126
Figure 5.6.	Forecast prices of S&P 500 by using GBM-STO and GFBM-STO vs actual prices .....	127
Figure 5.7.	Daily adjust price series of SSE from 5 <sup>th</sup> January 2015 to 31 <sup>st</sup> December 2015.....	128
Figure 5.8.	Daily returns SSE from 5 <sup>th</sup> January 2015 to 31 <sup>st</sup> December 2015....	129
Figure 5.9.	Forecast prices of SSE by using GBM-S and GFBM-S vs actual prices.....	138
Figure 5.10.	Forecast prices of SSE by using GBM-L and GFBM-L vs actual prices.....	139
Figure 5.11.	Forecast prices of SSE by using GBM-STO and GFBM-STO vs actual prices.....	140
Figure 5.12.	Daily adjust price series of KLCI from 2 <sup>nd</sup> January 2015 to 31 <sup>st</sup> December 2015.....	141
Figure 5.13.	Daily returns SSE KLCI from 2 <sup>nd</sup> January 2015 to 31 <sup>st</sup> December 2015 .....	142
Figure 5.14.	Forecast prices of KLCI by using GBM-S and GFBM-S vs actual prices.....	152

Figure 5.15.	Forecast prices of KLCI by using GBM-L and GFBM-L vs actual prices.....	153
Figure 5.16.	Forecast prices of KLCI using by GBM-HLC and GFBM-HLC vs actual prices.....	154
Figure 5.17.	Forecast prices of KLCI by using GBM-STO and GFBM-STO vs actual prices.....	155
Figure 6.1.	Daily closed price series of KLCI from 3 <sup>rd</sup> January 2005 to 29 <sup>th</sup> December 2006.....	161
Figure 6.2.	Daily return series of KLCI from 3 <sup>rd</sup> January 2005 to 29 <sup>th</sup> December 2006.....	161
Figure 6.3.	European call option prices using different methods with maturity time 15 days.....	165
Figure 6.4.	European call option prices using different methods with maturity time 30 days.....	166
Figure 6.5.	European call option prices using different methods with maturity time 45 days.....	166
Figure 6.6.	European call option prices using different methods with maturity time 60 days.....	167
Figure 6.7.	Daily adjust price series of PRPFX from 1 <sup>st</sup> January 2015 to 31 <sup>st</sup> December 2015.....	173
Figure 6.8.	Daily returns series of PRPFX from 1 <sup>st</sup> January 2015 to 31 <sup>st</sup> December 2015.....	173
Figure 6.9.	VaR of PRPFX with $q = 0.01$ .....	175
Figure 6.10.	VaR of PRPFX with $q = 0.05$ .....	176
Figure 6.11.	VaR of PRPFX with $q = 0.1$ .....	176
Figure 6.12.	Historical exchange rates between USD and MYR from 2 <sup>nd</sup> January 2015 to 31 <sup>st</sup> December 2015 .....	179
Figure 6.13.	Daily returns series of exchange rate between USD and MYR from 2 <sup>nd</sup> January 2015 to 31 <sup>st</sup> December 2015 .....	179
Figure 6.14.	Forecast exchange rates vs actual price (constant volatility case)....	186
Figure 6.15.	Forecast exchange rates vs actual price (STO-1 case).....	187
Figure 6.16.	Forecast exchange rates vs actual price (STO-2 case).....	187

Figure 6.17. Forecast exchange rates vs actual price (STO-3 case).....	188
Figure 6.18. Quarterly house price index in the UK from 4Q73 to 1Q17. ....	191
Figure 6.19. Quarterly return of house price index in the UK from 4Q73 to 1Q17.....	191
Figure 6.20. Comparison between the levels of potential losses in the first six years.....	194



## **List of Appendices**

Appendix A	Flowchart of Coding.....	214
Appendix B	Standard Simulation .....	218
Appendix C	Simulation with Segmentation.....	224



## List of Abbreviations

<b>AR</b>	Autoregressive Process
<b>ARCH</b>	Autoregressive Conditional Heteroscedasticity
<b>ARFIMA</b>	Autoregressive Fractionally Integrated Moving Average
<b>ARIMA</b>	Autoregressive Integrated Moving Average
<b>ARSV</b>	Autoregressive Stochastic Volatility
<b>BM</b>	Brownian Motion
<b>BS</b>	Black–Scholes
<b>CIR</b>	Cox–Ingersoll–Ross
<b>CMLE</b>	Complete Maximum Likelihood Estimation
<b>DE</b>	Differential Evolution
<b>EBSCO</b>	Elton Bryson Stephens Company
<b>EMM</b>	Efficient Method of Moments
<b>FBM</b>	Fractional Brownian Motion
<b>FBS</b>	Fractional Black–Scholes
<b>GFBM</b>	Geometric Fractional Brownian Motion
<b>FGN</b>	Fractional Gaussian Noise
<b>FOU</b>	Fractional Ornstein Uhlenbeck
<b>FSDE</b>	Fractional Stochastic Differential Equation
<b>GARCH</b>	Generalized Autoregressive Conditional Heteroscedasticity
<b>GBM</b>	Geometric Brownian Motion
<b>GMM</b>	Generalized method of moment
<b>GS</b>	Google Scholar
<b>H</b>	Hurst
<b>JP</b>	Jump
<b>KLCI</b>	Kuala Lumpur Composite Index
<b>LMSV</b>	Long Memory Stochastic Volatility
<b>MAPE</b>	Mean Absolute Percentage Error
<b>MBI</b>	Moment Based Inference
<b>MCMC</b>	Markov Chain Monte Carlo

<b>MLE</b>	Maximum Likelihood Estimation
<b>MM</b>	Method of Moments
<b>MSE</b>	Mean Square Error
<b>OU</b>	Ornstein– Uhlenbeck
<b>R/S</b>	Rescale / Range
<b>RS</b>	Random Search
<b>S &amp;P 500</b>	Standard and Poor's 500
<b>S.V</b>	SciVerse
<b>SA</b>	Simulated Annealing
<b>SABR</b>	Stochastic Alpha–Beta–Rho
<b>SBI</b>	Simulation Based Inference
<b>SDE</b>	Stochastic Differential Equation
<b>SV</b>	Stochastic Volatility
<b>Var</b>	Variance



# **CHAPTER ONE**

## **INTRODUCTION**

### **1.1 Research Background**

Volatility has been actively discussed in time series econometrics and economic forecasting in recent years. Volatility explains the variations witnessed in some phenomena over time. In economics, it is used to describe variability of random component of a time series. In financial economics, volatility is defined as the standard deviation of a random Wiener driven component in a continuous time diffusion model.

In the last decades, two main classes of volatility models have been developed: the generalized autoregressive conditional Heteroscedasticity (GARCH) and the stochastic volatility (SV) model. These classes were developed in order to capture time-varying autocorrelation, i.e. the correlation between values of the process at different points in time.

To begin, in 1982 Engle introduced autoregressive conditional heteroscedasticity (ARCH) model to estimate conditional variance of the sequence of increasing price of the United Kingdom's financial environment. This model was developed by prior assumption that the variance of random errors was related to the previous random, with inclusion of the conditional variance and mean in equation. Four years later, the extension of ARCH was proposed by Bollerslev (1986), known as generalized autoregressive conditional heteroscedasticity (GARCH) model. This model adds the memory of past variances to the model which is useful in modeling and forecasting

The contents of  
the thesis is for  
internal user  
only

## REFERENCES

- Abidin, S. N. Z., & Jaffar, M. M. (2012). A review on Geometric Brownian Motion in forecasting the share prices in Bursa Malaysia. *World Applied Sciences Journal*, 17, 87-93.
- Abidin, S. N. Z., & Jaffar, M. M. (2014). Forecasting share prices of small size companies in bursa Malaysia using geometric Brownian motion. *Applied Mathematics & Information Sciences*, 8(1), 107-112.
- Abken, P. A., & Nandi, S. (1996). Options and volatility. *Economic Review-Federal Reserve Bank of Atlanta*, 81, 21-35.
- Ahlip, R., & Rutkowski, M. (2016). Pricing of foreign exchange options under the MPT stochastic volatility model and the CIR interest rates. *The European Journal of Finance*, 22(7), 551-571.
- Aït-Sahalia, Y., & Lo, A. W. (1998). Nonparametric estimation of state–price densities implicit in financial asset prices. *The Journal of Finance*, 53(2), 499-547.
- Alòs, E., Mazet, O., & Nualart, D. (2000). Stochastic calculus with respect to fractional Brownian motion with Hurst parameter lesser than  $\frac{1}{2}$ . *Stochastic Processes and their Applications*, 86(1), 121-139.
- Andersen, T. G., & Sørensen, B. E. (1996). GMM estimation of a stochastic volatility model: A Monte Carlo study. *Journal of Business and Economic Statistics*, 14(3), 328-352.
- Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2001). The distribution of realized exchange rate volatility. *Journal of the American statistical association*, 96(453), 42-55.
- Asai, M. (2008). Autoregressive stochastic volatility models with heavy-tailed distributions: A comparison with multifactor volatility models. *Journal of Empirical Finance*, 15(2), 332-341.
- Ash, R. B., & Doleans-Dade, C. (2000). *Probability and measure theory*. San Diego: Academic Press.
- Bakshi, G., Cao, C., & Chen, Z. (2000). Pricing and hedging long-term options. *Journal of Econometrics*, 94, 277-318.
- Bardhan, A., Karapandža, R., & Urošević, B. (2006). Valuing mortgage insurance contracts in emerging market economies. *The Journal of Real Estate Finance and Economics*, 32(1), 9-20.

- Barndorff - Nielsen, O. E., & Shephard, N. (2001). Non - Gaussian Ornstein–Uhlenbeck - based models and some of their uses in financial economics. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 63(2), 167-241.
- Barndorff - Nielsen, O. E., & Shephard, N. (2002). Estimating quadratic variation using realized variance. *Journal of Applied Econometrics*, 17(5), 457-477.
- Bates, D. S. (1996). Jumps and stochastic volatility: Exchange rate processes implicit in deutsche mark options. *Review of Financial Studies*, 9, 69-107.
- Benavides, G. (2004), “Predictive accuracy of futures option implied volatility: the case of the exchange rate futures Mexican peso – US dollar”, working paper.
- Biagini, F., Hu, Y., Øksendal, B., & Zhang, T. (2008). *Stochastic calculus for fractional Brownian motion and applications*. Springer Science.
- Billingsley, P. (1999). *Convergence of probability measures* . Wiley.
- Black, F., & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *The Journal of Political Economy*, 81(3), 637-654.
- Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307-327.
- Breidt, F. J., Crato, N., & De Lima, P. (1998). The detection and estimation of long memory in stochastic volatility. *Journal of Econometrics*, 83(1), 325-348.
- Brockwell, P. J. (2001). Lévy–driven CARMA processes. *Annals of the Institute of Statistical Mathematics*, 53(1), 113-124.
- Brockwell, P. J., & Davis, R. A. (1991). *Time Series: Theory and Methods*. Springer.
- Chan, N. H., & Wong, H. Y. (2006). Black–Scholes Model and Option Pricing. *Simulation Techniques in Financial Risk Management*, 57-74.
- Chandra, T. K. (2012). *The Borel–Cantelli Lemma*. Springer Science & Business Media.
- Chen, C. C., Lin, S. K., & Chen, W. S. (2013). *Mortgage insurance premiums and business cycle*. Tunghai University working paper.
- Chronopoulou, A., & Viens, F. G. (2012 a). Estimation and pricing under long–memory stochastic volatility. *Annals of Finance*, 8(2), 379-403.

- Chronopoulou, A., & Viens, F. G. (2012 b). Stochastic volatility and option pricing with long-memory in discrete and continuous time. *Quantitative Finance*, 12(4), 635-649.
- Chuang, M. C., Yang, W. R., Chen, M. C., & Lin, S. K. (2017). Pricing mortgage insurance contracts under housing price cycles with jump risk: evidence from the UK housing market. *The European Journal of Finance*, 1-38.
- Cinlar, E. (2013). *Introduction to Stochastic Processes*. Courier Corporation
- Coculescu, D., & Nikeghbali, A. (2010). Filtrations. *Encyclopedia of Quantitative Finance*, 2461-2488.
- Comte, F. & Renault, E. (1998). Long memory in continuous-time stochastic volatility models. *Mathematical Finance*, 8(4), 291-323.
- Comte, F., Coutin, L., & Renault, É. (2012). Affine fractional stochastic volatility models. *Annals of Finance*, 8(2), 337-378.
- Cordell, L. R., & King, K. K. (1995). A market evaluation of the risk-based capital standards for the US financial system. *Journal of Banking & Finance*, 19(3), 531-562.
- Cox, J. C., Ross, S. A., & Rubinstein, M. (1979). Option pricing: A simplified approach. *Journal of Financial Economics*, 7(3), 229-263.
- Diebold F.S. & M. Nerjove. (1989). The dynamics of exchange rate volatility: A multivariate latent factor ARCH model, *Journal of Applied Econometrics*, 4, 1-22.
- Dimson, E., & Marsh, P. (1995). Capital requirements for securities firms. *The Journal of Finance*, 50(3), 821-851.
- Dung, N. T. (2011). Semimartingale approximation of fractional Brownian motion and its applications. *Computers & Mathematics with Applications*, 61(7), 1844-1854.
- Dung, N. T., & Thao, T. H. (2010). An approximate approach to fractional stochastic integration and its applications. *Brazilian Journal of Probability and Statistics*, 24(1), 57-67.
- Durbin, J., & Koopman, S. J. (2001). *Time Series Analysis by State Space Methods*. Oxford University Press.
- Elerian, O., Chib, S., & Shephard, N. (2004). Likelihood inference for discretely observed nonlinear diffusions. *Econometrica*, 69(4), 959-993.

- Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50(4), 987-1007.
- Eraker, B. (2001). MCMC analysis of diffusion models with application to finance. *Journal of Business and Economic Statistics*, 19(2), 177-191.
- Fernández-Villaverde, J., Guerrón-Quintana, P., & Rubio-Ramírez, J. F. (2015). Estimating dynamic equilibrium models with stochastic volatility. *Journal of Econometrics*, 185(1), 216-229.
- Fiorentini, G., Sentana, E., & Shephard, N. (2004). Likelihood - Based Estimation of Latent Generalized ARCH Structures. *Econometrica*, 72(5), 1481-1517.
- Fleming, J., & Kirby, C. (2003). A closer look at the relation between GARCH and stochastic autoregressive volatility. *Journal of Financial Econometrics*, 1(3), 365-419.
- Fouque, J. P., Papanicolaou, G., & Sircar, K. R. (2000). *Derivatives in financial markets with stochastic volatility*. Cambridge University Press.
- Gianin, E. R., & Sgarra, C. (2013). Binomial Model for Option Pricing. *Mathematical Finance: Theory Review and Exercises*, 31-60.
- Gjerde, Ø., & Semmen, K. (1995). Risk-based capital requirements and bank portfolio risk. *Journal of Banking & Finance*, 19(7), 1159-1173.
- Gong, X., & Zhuang, X. (2017). Pricing foreign equity option under stochastic volatility tempered stable Lévy processes. *Physica A: Statistical Mechanics and its Applications*, 483, 83-93.
- Gozgor, G. (2013). The application of stochastic processes in exchange rate forecasting: Benchmark test for the EUR/USD and the USD/TRY. *Economic Computation and Economic Cybernetics Studies and Research*, 47 (2), 225-246.
- Grau-Carles, P. (2000). Empirical evidence of long-range correlations in stock returns. *Physica A: Statistical Mechanics and its Applications*, 287(3), 396-404.
- Hagan, P. S., Kumar, D., Lesniewski, A. S., & Woodward, D. E. (2002). Managing smile risk. *The Best of Wilmott*, 1, 249-296.
- Hamilton, J.D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, 57(2), 357-384.
- Han, C. H., Liu, W. H., & Chen, T. Y. (2014). VaR/CVaR estimation under stochastic volatility models. *International Journal of Theoretical and Applied Finance*, 17(2), 1-35.

- Harris, J. W., & Stöcker, H. (1998). *Handbook of mathematics and computational science*. Springer Science & Business Media.
- Harvey, A. C. (1998). Long memory in stochastic volatility. In J. Knight and S. Satchell (Eds.), *Forecasting Volatility in Financial Markets*, 307-320.
- Harvey, A., Ruiz, E., & Shephard, N. (1994). Multivariate stochastic variance models. *The Review of Economic Studies*, 61(2), 247-264.
- He, S. W., & Yan, J. A. (1992). *Semimartingale Theory and Stochastic Calculus*. New York: CRC Press.
- Heston, S. L. (1993). A closed-form solution for options with stochastic volatility with applications to bond and currency options. *Review of Financial Studies*, 6(2), 327-343.
- Hull, J. & White, A. (1987). The pricing of options on assets with stochastic volatilities. *Journal of Finance*, 42, 281-300.
- Hyndman, R. J., & Fan, Y. (1996). Sample quantiles in statistical packages. *The American Statistician*, 50(4), 361-365.
- Ibrahim, M. (1999). Macroeconomic variables and stock prices in Malaysia: An empirical analysis. *Asian Economic Journal*, 13(2), 219-231.
- Intarasit, A., & Sattayatham, P. (2010). A geometric Brownian motion model with compound Poisson process and fractional stochastic volatility. *Advances and Applications in Statistics*, 16(1), 25-47.
- Jacquier, E., Polson, N. G., & Rossi, P. E. (2004). Bayesian analysis of stochastic volatility models with fat-tails and correlated errors. *Journal of Econometrics*, 122(1), 185-212.
- Jennings, L.S & Teo, K.L. (1990). A computational algorithm for functional inequality constrained optimization problems. *Automatica*, 26, 371-375.
- Johnson, H., & Shanno, D. (1987). Option pricing when the variance is changing. *Journal of Financial and Quantitative Analysis*, 143-151.
- Keogh, E., Chu, S., Hart, D., & Pazzani, M. (2004). Segmenting time series: A survey and novel approach. *Data Mining in Time Series Databases*, 57, 1-22.
- Kermiche, L. (2014). Too Much Of A Good Thing? A Review Of Volatility Extensions In Black-Scholes. *Journal of Applied Business Research*, 30(4), 1171-1182.

- Kim, B., & Wee, I. S. (2014). Pricing of geometric Asian options under Heston's stochastic volatility model. *Quantitative Finance*, 14(10), 1795-1809.
- Kim, S., Shephard, N., & Chib, S. (1998). Stochastic volatility: likelihood inference and comparison with ARCH models. *The Review of Economic Studies*, 65(3), 361-393.
- King, M., E. Sentana, & S. Wadhwani (1994). Volatility and links between national stock markets. *Econometrica*, 62, 901-933.
- Knapp, A. W. (2005). *Basic real analysis*. Springer Science & Business Media.
- Kolmogorov, A. N. (1940). Curves in Hilbert space which are invariant with respect to a one-parameter group of motions. In *Doklady Akad. Nauk*, 26, 6-9.
- Kukush, Mishura,Y., & Valkeila,E. (2005). Statistical inference with fractional brownian motion. *Statistical Inference for Stochastic Processes*, 8, 71-93.
- Lam, K., Chang, E., & Lee, M. C. (2002). An empirical test of the variance gamma option pricing model. *Pacific-Basin Finance Journal*, 10(3), 267-285
- Lawrence, K. D., Klimberg, R. K., & Lawrence, S. M. (2009). *Fundamentals of forecasting using excel*. New York: Industrial Press.
- Lin, Z., & Bai, Z. (2010). *Probability inequalities*. Springer Science & Business Media.
- Mabrouk, S. (2017). Volatility Modelling and Parametric Value-At-Risk Forecast Accuracy: Evidence from Metal Products. *Asian Economic and Financial Review*, 7(1), 63-80.
- Malkiel, B. G. (1989). Is the stock market efficient?. *Science*, 1313-1318.
- Mandelbrot, B. B. (1963). The variation of certain speculative prices. *J. Business*, 36, 394-419.
- Mandelbrot, B. B., & Van Ness, J. W. (1968). Fractional Brownian motions, fractional noises and applications. *SIAM review*, 10(4), 422-437.
- Mansaku, I., Mansaku, S., & Tampakoudis, I. (2016). An empirical comparison of the major stock exchanges: NYSE, NASDAQ and LSE in perspective. *Academic Journal of Interdisciplinary Studies*, 5(3), 406-415.
- Massoulie, L., & Simonian, A. (1999). Large buffer asymptotics for the queue with fractional Brownian input. *Journal of Applied Probability*, 36(3), 894–906.

- Meddahi, N., 2001. *An eigenfunction approach for volatility modeling*. Working Paper, University of Montreal.
- Menkens, O. (2007). Value at risk and self-similarity. *Numerical methods for finance. Chapman & Hall/CRC Financial Mathematics Series*, 8, 225-253.
- Mishura, Y. (2008). *Stochastic Calculus for Fractional Brownian Motion and Related Processes*. Springer.
- Mishura, Y., & Swishchuk, A. (2010). Modeling and pricing of variance and volatility swaps for stochastic volatilities driven by fractional Brownian motion. *Applied Statistics, Actuarial and Financial Mathematics*, 52–67.
- Misiran, M. (2010). *Modeling and pricing financial assets under long memory processes* (Doctoral dissertation). Curtin University of Technology.
- Misiran, M., Zudi, L.U., Teo, K. L., & Grace, A. W. (2012). Estimating dynamic geometric fractional Brownian motion and its application to long-memory option pricing. *Dynamic Systems and Applications*, 21(1), 49–66.
- Mitra, S. (2011). A review of volatility and option pricing. *International Journal of Financial Markets and Derivatives*, 2(3), 149–179.
- Momani, S., Arqub, O. A., Al-Mezel, S., & Kutbi, M. (2016). Existence and uniqueness of fuzzy solutions for the nonlinear second-order fuzzy Volterra integrodifferential equations. *Journal of Computational Analysis & Applications*, 21(2), 213-227.
- Mörters, P., & Peres, Y. (2010). *Brownian motion*. Cambridge: Cambridge University Press.
- Murthy, U., Anthony, P., & Vighnesvaran, R. (2016). Factors affecting Kuala Lumpur Composite Index (KLCI) stock market return in Malaysia. *International Journal of Business and Management*, 12(1), 122-132.
- Narayan, O. (1998). Exact asymptotic queue length distribution for fractional brownian tra c. *Advances in Performance Analysis*, 1(1), 39-63.
- Nelder, J. A., & Mead, R. (1965). A simplex method for function minimization. *The Computer Journal*, 7(4), 308-313.
- Nicita, A. (2013). Exchange rates, international trade and trade policies. *International Economics*, 135, 47-61.

- Norros, I. (1995). On the use of fractional Brownian motion in the theory of connectionless networks. *Selected Areas in Communications, IEEE Journal on*, 13(6), 953-962.
- Norros, I. (1997). Four approaches to the fractional Brownian storage. *Fractals in Engineering*. 1(1), 154-169.
- Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural equation modeling*, 14(4), 535-569.
- Oguntuase, J. A. (2001). On an inequality of Gronwall. *Journal of Inequalities in Pure and Applied Mathematics*, 2(1), 9.
- Oksendal, B. (2000). *Stochastic Differential Equations: An Introduction with Applications*. Springer.
- Omar, A. and Jaffar, M.M.(2011). Comparative Analysis of Geometric Brownian Motion Model in forecasting FBMHS and FBMKLCI Index in Bursa Malaysia. *IEEE symposium on Business, Engineering and industrial Applications, Langkawi, Malaysia*, 157- 161.
- Painter, S. (1998). Numerical method for conditional simulation of Levy random fields. *Mathematical Geology*, 30(2), 163-179.
- Pakdel, M. (2016). *Essays in financial economics* (Doctoral dissertation, Northern Illinois University)
- Patrick, B. (1995). *Probability and measure*. John Wiley & Sons.
- Pliepanich, T., Sattayatham, P., & Thao, T. H. (2009). Fractional integrated GARCH diffusion limit models. *Journal of the Korean Statistical Society*, 38(3), 231-238.
- Racine, R. (2011). Estimating the Hurst exponent. MOSAIC Group: Bachelor thesis, Zurich.
- Rahman, S. M. B. A., Hatta, S. A. B. M., & Ismail, H. F. B. (2013). Macroeconomic Variables of Stock Prices (KLCI). *International Conference on Financial Criminology*, 233-249.
- Rastrigin, L. A. (1964). Convergence of random search method in extremal control of many-parameter system. *Automation and Remote Control*, 24(11), 1337.

- Rejichi, I. Z., & Aloui, C. (2012). Hurst exponent behavior and assessment of the MENA stock markets efficiency. *Research in International Business and Finance*, 26(3), 353–370.
- Roberts, G. & Stramer, O. (2001). On inference for partial observed nonlinear diffusion models using the metropolis–hastings algorithm. *Biometrika*, 88(3), 603–621.
- Ross, S. M. (1997). Introduction to probability models. *Academic Press*.
- Ross, S. M. (1999). *An introduction to mathematical finance: options and other topics*. Cambridge University Press.
- Schöbel, R., & Zhu, J. (1999). Stochastic volatility with an Ornstein–Uhlenbeck process: an extension. *European Finance Review*, 3(1), 23-46.
- Scott, L. O. (1987). Option pricing when the variance changes randomly: Theory, estimation, and an application. *Journal of Financial and Quantitative analysis*, 22(4), 419-438.
- Shen, F., Chao, J., & Zhao, J. (2015). Forecasting exchange rate using deep belief networks and conjugate gradient method. *Neurocomputing*, 167, 243-253.
- Shiryayev, A. N. (1999). *Essentials of stochastic finance: facts, models, theory*. World Scientific.
- Shumway, R. H. & Stoffer, D. S. (2006). *Time Series Analysis and its Applications: With R Examples*. Springer
- Stein, E. M. & J. Stein (1991). Stock price distributions with stochastic volatility: an analytic approach. *Review of Financial Studies*, 4, 727-752.
- Stein, J.C.(1989). Overreactions in the options market. *Journal of Finance*, 44, 1011-1023.
- Storn, R., & Price, K. (1995). Differential evolution—a simple and efficient adaptive scheme for global optimization over continuous spaces: technical report TR-95-012. *International Computer Science, Berkeley, California*.
- Storn, R., & Price, K. (1997). Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces. *Journal of global optimization*, 11(4), 341-359.
- Taylor, H. M., & Karlin, S. (2014). *An introduction to stochastic modeling*. Academic Press.

- Taylor, S. J. (1982). Financial returns modelled by the product of two stochastic processes—a study of the daily sugar prices 1961–75. *Time Series Analysis: Theory and Practice*, 1, 203-226.
- Taylor, S. J. (1986). *Modelling Financial Time Series*. John Wiley & Sons, New Jersey.
- Thao, T. H. (2006). An approximate approach to fractional analysis for finance. *Nonlinear Analysis: Real World Applications*, 7(1), 124-132.
- Thao, T. H. (2014). On some classes of fractional stochastic dynamical systems. *East-West Journal of Mathematics*, 15(1), 54-69.
- Thao, T. H., & Christine, T. A. (2003). Evolution des cours gouvernée par un processus de type ARIMA fractionnaire. *Studia Babes-Bolyai, Mathematica*, 38(2), 107-115.
- Thao, T. H., Sattayatham, P., & Plienpanich, T. (2008). On the fractional stochastic filtering. *Studia Babes-Bolyai, Mathematica*, 53(4), 97-108.
- Tian, Y. (1999). A flexible binomial option pricing model. *Journal of Futures Markets*, 19(7), 817-843.
- Tien, D. N. (2013 a). A stochastic Ginzburg–Landau equation with impulsive effects. *Physica A: Statistical Mechanics and its Applications*, 392(9), 1962-1971.
- Tien, D. N. (2013 b). The existence of a positive solution for a generalized delay logistic equation with multifractional noise. *Statistics & Probability Letters*, 83(4), 1240-1246.
- Todorov, V., & Tauchen, G. (2006). Simulation methods for Lévy–driven continuous–time autoregressive moving average (CARMA) stochastic volatility models. *Journal of Business and Economic Statistics*, 24(4), 455-469.
- Tofallis, C. (2015). A better measure of relative prediction accuracy for model selection and model estimation. *Journal of the Operational Research Society*, 66(8), 1352-1362.
- Tripathy, S., & Rahman, A. (2013). Forecasting daily stock volatility using GARCH model: A comparison between BSE and SSE. *IUP Journal of Applied Finance*, 19(4), 71-83.
- Vasicek, O. (1977). An equilibrium characterization of the term structure. *Journal of Financial Economics*, 5(2), 177–188.

- Vierthauer, R. (2010). *Hedging in affine stochastic volatility models* (Doctoral dissertation), Christian-Albrechts Universität Kiel.
- Walsh, D. M., & Tsou, G. Y. G. (1998). Forecasting index volatility: Sampling interval and non-trading effects. *Applied Financial Economics*, 8(5), 477-485.
- Wang, X., & Zhang, W. (2014). Parameter estimation for long-memory stochastic volatility at discrete observation. In *Abstract and Applied Analysis*, (2014). Hindawi Publishing Corporation.
- Wang, X., Xie, D., Jiang, J., Wu, X., & He, J. (2017). Value-at-Risk estimation with stochastic interest rate models for option-bond portfolios. *Finance Research Letters*, 21, 10-20.
- Weise, T. (2009). Global optimization algorithms—theory and application. *Self-Published*, 25–26.
- Wiersema, U. F. (2008). *Brownian motion calculus*. John Wiley & Sons.
- Wiggins, J. B. (1987). Option values under stochastic volatility: Theory and empirical estimates. *Journal of Financial Economics*, 19(2), 351–372.
- Willinger, W., Taqqu, M. S., & Teverovsky, V. (1999). Stock market prices and long-range dependence. *Finance and Stochastics*, 3(1), 1-13.
- Wright, M. H. (2010). Nelder, Mead, and the other simplex method. *Documenta Mathematica*, 7, 271-276.
- Wu P., & Elliott, R. J. (2017). A simple efficient approximation to price basket stock options with volatility smile. *Annals of Finance*, 13(1), 1-29.
- Xiao, W., Zhang, W., & Zhang, X. (2015). Parameter identification for the discretely observed geometric fractional Brownian motion. *Journal of Statistical Computation and Simulation*, 85(2), 269-283
- Yalincak, H. O. (2012). *Criticism of the Black-Scholes Model: But Why is it Still Used? (The Answer is Simpler than the Formula)*. Rochester, NY: Social Science Research Network
- Yao, S., Luo, D., & Morgan, S (2008). *Shanghai stock exchange composite index and bank stock prices in China: A Causality Analysis* (Discussion paper). University of Nottingham.

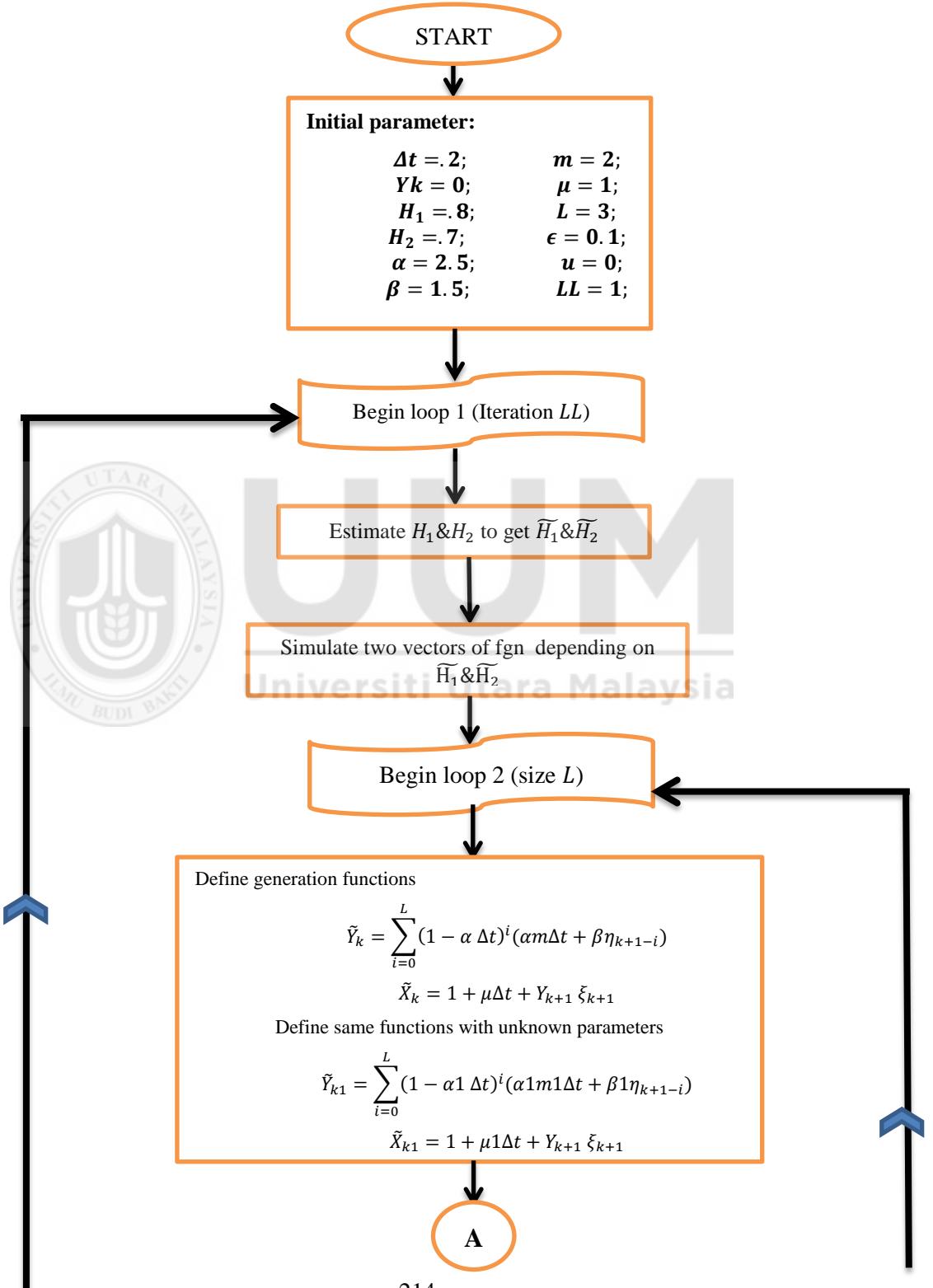
Ye, Y. (2017). Study on Exchange Rate Forecasting Using Recurrent Neural Networks. *International Journal of Economics, Finance and Management Sciences*, 5(6), 300-303.

Zhang, K., & Hyvarinen, A. (2012). Source separation and higher-order causal analysis of MEG and EEG. *arXiv preprint arXiv:1203.3533*.



## Appendix A

### Flowchart for Parameters Estimation



A

Compute the following covariance function:

$$\gamma_{\xi}(n) = \frac{1}{2}(|(n+1)\Delta t|^{2H_1} + |(n-1)\Delta t|^{2H_1} - 2|n\Delta t|^{2H_1})$$

$$\gamma_{\eta}(n) = \frac{1}{2}(|(n+1)\Delta t|^{2H_2} + |(n-1)\Delta t|^{2H_2} - 2|n\Delta t|^{2H_2})$$

$$\gamma_{\tilde{\gamma}}(n) = \beta^2 \sum_{i=0}^L \sum_{j=0}^L (1 - \alpha \Delta t)^{i+j} \gamma_{\eta}(n+i-j)$$

Construct the following matrices:

$$\Gamma_{n-1} = \{\gamma(k-j)\}_{j,k=1}^{n-1} \quad \& \quad \Gamma_{n-1}^{-1}$$

$$\tilde{\gamma}_{n-1} = (\gamma_{\tilde{x}}(n-1), \dots, \gamma_{\tilde{x}}(1))' \quad \& \quad \tilde{\gamma}_{n-1}'$$

$$\gamma_n = (\gamma(1), \dots, \gamma(n))'$$

$$\Gamma_n = \begin{bmatrix} \Gamma_{n-1} & \tilde{\gamma}_{n-1} \\ \tilde{\gamma}_{n-1}' & \tilde{\gamma}_{\tilde{x}}(0) \end{bmatrix}$$

$$\phi_n = \Gamma_n^{-1} \gamma_n$$

$$\Gamma_n^{-1}$$

$$= \begin{bmatrix} I & -\Gamma_{n-1}^{-1} \tilde{\gamma}_{n-1} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \Gamma_{n-1}^{-1} & 0 \\ 0 & (\gamma_{\tilde{x}}(0) - \tilde{\gamma}_{n-1}' \Gamma_{n-1}^{-1} \tilde{\gamma}_{n-1})^{-1} \end{bmatrix} \begin{bmatrix} I & 0 \\ -\tilde{\gamma}_{n-1}' \Gamma_{n-1}^{-1} & 1 \end{bmatrix}$$

$$\text{Compute } v_T^2 = \gamma(0) - \gamma_T' \Gamma_T^{-1} \gamma_T$$

B

B

Construct the following matrices

$$A = \begin{bmatrix} 1 & 0 & \dots & 0 \\ -\phi_{11} & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ -\phi_{(T-1)1} & -\phi_{(T-1)2} & \dots & -\phi_{(T-1)(T-1)} \end{bmatrix}$$

$$KK = \begin{bmatrix} \frac{1}{v_1^2} & 0 & \dots & 0 \\ 0 & \frac{1}{v_2^2} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \frac{1}{v_n^2} \end{bmatrix}$$

Compute:

$$\Sigma_T^{-1} = A' \cdot KK \cdot A$$

$$\det(\Sigma_T) = \prod_{i=1}^T E(\varepsilon_i)^2 = \prod_{i=1}^T v_i^2$$

Find the value of:

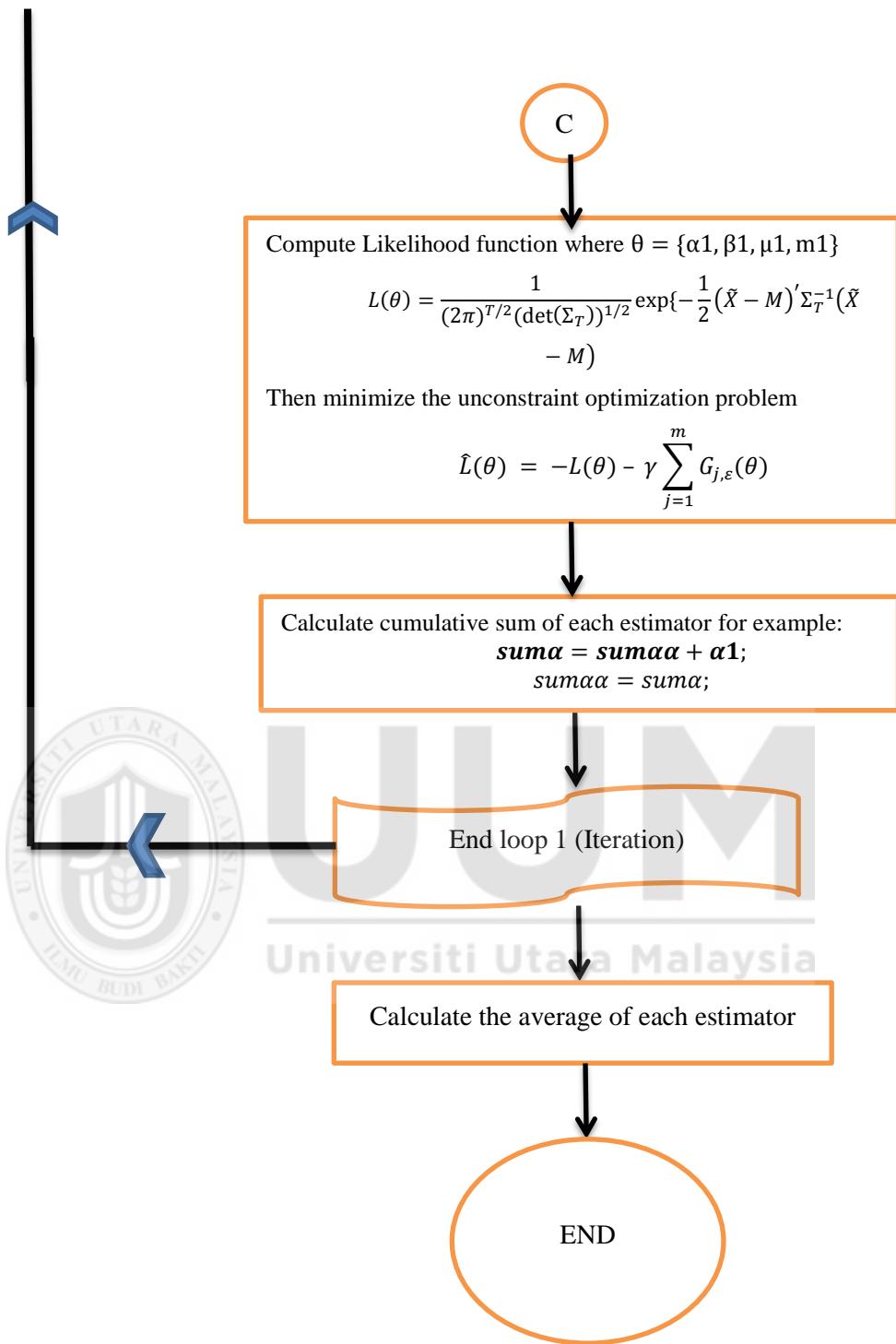
$$g_1(\theta) = -E(\tilde{X} - \mu)^2 = -\gamma_{\tilde{X}}(n);$$

$$g_2(\theta) = -v^2 = -\left\{ \sum_{i=1}^L (1 - \alpha \Delta t)^i (\alpha m \Delta t) \right\}^2 \Delta t^{2H1} - \sum_{i=1}^L (1 - \alpha \Delta t)^{2i} \beta^2 \Delta t^{2(H2+H1)};$$

$$G_{i,\varepsilon}(\theta) = \begin{cases} g_i & , g_i > \varepsilon \\ \frac{(g_i - \varepsilon)^2}{4\varepsilon} & , -\varepsilon < g_i < \varepsilon \\ 0 & , g_i < -\varepsilon \end{cases}$$

End loop 2 ( size L)

C



## Appendix B

### Standard Simulation for Parameters Estimation

```
Δt=.2;
H1=.8;
H2=.7;
α=2.5;
m=2;
β=1.5;
μ=1;
ε=0.1;
l=0;
t=0;
u=0;
v=0;
c=0;
e=0;
f=0;
RR=100;
NN=10;
sumαhut1=0;
summhut1=0;
sumβhut1=0;
sumμhut1=0;
H11=0.8;
H22=0.7;
For[r=1,r<=RR,r++,
“Simulate a fractional Brownian motion process–1st one “;
data1=RandomFunction[FractionalBrownianMotionProcess[H1],{0,1,0.001}];
“finds the parameter estimates for the fbm process(H1) from data1”;
EH1=FindProcessParameters[data1,FractionalBrownianMotionProcess[h]];
H11=EH1[[1,2]];
“Simulate a fractional Brownian motion process–2nd one “;
data2=RandomFunction[FractionalBrownianMotionProcess[H2],{0,1,0.001}];
”finds the parameter estimates for the fbm process(H2) from data2”;
```

```

EH2=FindProcessParameters[data2,FractionalBrownianMotionProcess[h]];
H22=EH2[[1,2]];
“simulate fgn”;
SimulateFGN[H_,n_]:=Module[{N,ac},N=2^Ceiling[Log[2,n-1]];
ac=Table[FGNAcf[k,H],{k,0,N }];
Take[SimulateGLP[ac,n]];SimulateGLP[γ_]:=Module[{m=Length[γ],n,c,g,Z,
Ncap},n=2^Ceiling[Log[2,m-1]];acvf=If[n==m-
1,γ,PadRight[γ,n+1]];Ncap=2*n;
c=Join[acvf,Rest[Reverse[Rest[acvf]]]];
g=Re[Fourier[c,FourierParameters→{1,-1}]];
Z=RandomVariate[NormalDistribution[0,1],Ncap-2];
Z=(Complex[Sequence@@#1]&)/@Partition[Z,2];
Z=Flatten[{RandomVariate[NormalDistribution[0,Sqrt[2]]],Z,RandomVariate
[NormalDistribution[0,Sqrt[2]]],Reverse[Conjugate[Z]]}];
Take[Re[InverseFourier[Sqrt[g]*Z,FourierParameters→{0,-1}]],m]/Sqrt[2]];
FGNAcf[k_,H_]:=Module[{},0.5*(Abs[k+1.0]^(2.0*H)-
2*Abs[k]^(2.0*H)+Abs[k-1.0]^(2.0*H))];
“fgn at H=.65 and n=20”;
SmH111=SimulateFGN[H11,RR+1];
“fgn at H=.9 and n=20”;
SmH222=SimulateFGN[H22,RR+1];

```

```

n=2;
While[n<=NN,
Clear[α1,m1,β1,μ1];
sumαα=0;
sumββ=0;
sumμμ=0;
summm=0;

```

```

Yk11[n_]:= Sum[((1 - α1 Δt)^i (α1 m1 Δt + β1 SmH2[Abs[i + 1]])), {i, 0, ∞}];
Xk1[n_]:=1+μ1 Δt+SmH1[[n]]*
Sum[((1 - α1 Δt)^i (α1 m1 Δt + β1 SmH2[Abs[i + 1]])), {i, 0, ∞}];
Yk[n_]:= Sum[(1 - α Δt)^i (α m Δt + β SmH2[Abs[i + 1]])), {i, 0, ∞}];

```

```

Xk[n_]:=1+μ Δt+Yk[n]*SmH1[[n]];
mu[n_]:=Mean[Table[Xk1[i],{i,1,n}]];
X[n_]:=Table[Xk1[i],{i,1,n}]; XX[n_]:=Table[Xk[i],{i,1,n-1}]~Join~{Xk1[n]};
γξ[n_]:=1/2 (Abs[(n-1) Δt]2 H11+Abs[(n+1) Δt]2 H11-2 Abs[n Δt]2 H11);
γη[n_]:=1/2 (Abs[(n-1) Δt]2 H22+Abs[(n+1) Δt]2 H22-2 Abs[n Δt]2 H22);
γX[n_]:=Yk[n]2 γξ[n];
γY[n_]:= β2 Σi=0∞ Σj=0∞ (1 - α Δt)i+j γη[n + 1 - j];
Γn1[n_]:=Table[γX[i-j],{i,1,n-1},{j,1,n-1}];"Γn-1";
γn1[n_]:=Table[γX[n-i],{i,1,n-1},{j,1,1}];"γn-1";
γTn1[n_]:=Transpose[γn1[n]]; "γn-1 transpose";
γX0=γX[0];"γX(0)";
Γ[n_]:=ArrayFlatten[{{Γn1[n],γn1[n]},{γTn1[n],γX0}}];
invΓ[n_]:=Inverse[Γ[n]];
γ[n_]:=Table[{γX[i]},{i,1,n}];"γT in 3.27";
VT2[n_]:=Abs[γX[0]-Transpose[γ[n]].invΓ[n].γ[n]]; "3.27";
VT22[n_]:=ToExpression[StringReplace[ToString[VT2[n]],{"->",""}"->""}]];
invΓ[1]=1/γX0;
For[i=1,i<=n,i++,
φ[i_]:=invΓ[i].γ[i];
φ1[i_]:=Flatten[φ[i]];
For[j=1,j<=n,j++,
If[i==j,a[i,j]=1];
If[i<j,a[i,j]=0];
If[i>j,a[i,j]=- φ1[i-1][j]]
];
a[1,1]=1;
a[2,1]=-γX[1]/γX0;
];
A=Table[a[i,j],{i,1,n},{j,1,n}];
For[i=2,i<=n,i++,
For[j=2,j<=n,j++,
VT1=Abs[γX0-γX[1]* 1/γX0 *γX[1]];
d[1,1]=(1/VT1);

```

```

If[i==j,d[i,j]=1/VT22[i]];
If[i<j,d[i,j]=0];
If[i>j,d[i,j]=0];
]
];

KK=Table[If[i==1,d[i,j]=0,d[i,j]],{i,1,n},
{j,1,n}];
KK=Table[If[j==1,d[i,j]=0,d[i,j]],{i,1,n},
{j,1,n}];
d[1,1]=Abs[1/VT1];
KK=Table[d[i,j],{i,1,n},{j,1,n}];
segmainv[n_]:=SetPrecision[Transpose[A].KK.A ,5];
“segma[n_]:=PaddedForm[SetPrecision[Inverse[segmainv[n]],5],{5,5}]”;
DetKKK[n_]:=VT1 * $\prod_{i=1}^n$  VT2[i];
“define penalty function “;
g1[n_]:=- $\gamma$ X[n];
g2[n_]:= -  $\sum_{i=1}^L$   $(1 - \alpha \Delta t)^i (\alpha m \Delta t)^2 \Delta t^{2H11} - \sum_{i=1}^L (1 - \alpha \Delta t)^{2i} \beta^2 \Delta t^{2(H22+H11)}$ ;
G1[n_]:=Piecewise[{{ {g1[n],g1[n]> $\epsilon$ }, {(g1[n]- $\epsilon$ ) $^2/(4\epsilon)$ , $\epsilon < g1[n] < \epsilon$ }, {0,g1[n]<- $\epsilon$ }}];”3.36 w.r.t g1”;
G2[n_]:=Piecewise[{{ {g2[n],g2[n]> $\epsilon$ }, {(g2[n]- $\epsilon$ ) $^2/(4\epsilon)$ , $\epsilon < g2[n] < \epsilon$ }, {0,g2[n]<- $\epsilon$ }}];”3.36w.r.t g2”;
;n++];
“lhood[NN_]:=Log[PDF[MultinormalDistribution[Flatten[Table[mu[i],{i,1,NN}]],segma[NN]],X[NN]]]”;
lhood1[NN_]:=Log[Exp[-0.5* Transpose[Table[Xk1[i]-
mu[i],{i,1,NN}],{1}].segmainv[NN].Table[Xk1[i]-
mu[i],{i,1,NN}]]/ToExpression[StringReplace[ToString[(2 Pi) $^{\frac{NN}{2}}$ ]
DetKKK [NN] $^{\frac{1}{2}}$  ],{””->””,””->””}]]];
op=NMinimize[- lhood1[NN]- $\epsilon/4 \sum_{i=1}^{NN} G1[i] - \epsilon/4 \sum_{i=1}^{NN} G2[i]$ 
,{ $\alpha_1, m_1, \beta_1, \mu_1$ },WorkingPrecision->15,Method->”DifferentialEvolution”];
dd=op;
answer=op[[1]];
optimallu=u+1=answer;

```

var=dd[[2]];”the answer”;

```
αα=var[[1]];
ααα=αα[[2]];
suma=sumaα+ααα;
sumαα=suma;
```

```
mm=var[[2]];
mmm=mm[[2]];
summ=summm+mmm;
summm=summ;
```

```
ββ=var[[3]];
βββ=ββ[[2]];
sumβ=sumββ+βββ;
sumββ=sumβ;
```

```
μμ0=var[[4]];
μμμ=μμ0[[2]];
sumμ=sumμμ+μμμ;
sumμμ= sumμ;
```

```
“Print[dd];”;
sepvar=Table[var[[i,2]],{i,1,4}];
{ α1,m1,β1,μ1}=sepvar;
Clear[ α1,m1,β1,μ1];
Table[optimalli,{i,1,RR}];
H1hut=H11;
H1huttl=l+1=H1hut;
H2hut=H22;
H2huttt=t+1=H2hut;
αhut=sumaα/RR;
αhuttv=v+1=αhut;
mhut=summm/RR;
mhuttc=c+1=mhut;
βhut=sumββ/RR;
```



```
 $\beta_{hut}$ tte=e+1= $\beta_{hut}$ ;  
 $\mu_{hut}$ =sum $\mu\mu$ /RR;  
 $\mu_{hut}$ ttf=f+1= $\mu_{hut}$ ;  
Print[H1hut];  
Print[H2hut];  
Print[ $\alpha_{hut}$ ];  
Print[mhut];  
Print[ $\beta_{hut}$ ];  
Print[ $\mu_{hut}$ ];  
Print[">>>>>>>>>>>>>>>>>>"];  
];
```



## Appendix C

### Simulation with Segmentation for Parameters Estimation

```
Δt=.2;  
H1=.8;  
H2=.7;  
α=2.5;  
m=2;  
β=1.5;  
μ=1;  
ε=0.1;  
l=0;  
t=0;  
u=0;  
v=0;  
c=0;  
e=0;  
f=0;  
RR=100;  
JJ=10;  
NN=10;  
sumαhut1=0;  
summhut1=0;  
sumβhut1=0;  
sumμhut1=0;  
H11=0.8;  
H22=0.7;  
For[r=1,r<=RR,r++,  
“Simulate a fractional Brownian motion process –1st one “;  
data1=RandomFunction[FractionalBrownianMotionProcess[H1],{0,1,0.001}];  
“finds the parameter estimates for the fbm process(H1) from data1”;  
EH1=FindProcessParameters[data1,FractionalBrownianMotionProcess[h]];  
H11=EH1[[1,2]];  
“Simulate a fractional Brownian motion process–2nd one “;
```

```

data2=RandomFunction[FractionalBrownianMotionProcess[H2],{0,1,0.001}];  

"finds the parameter estimates for the fbm process(H2) from data2";  

EH2=FindProcessParameters[data2,FractionalBrownianMotionProcess[h]];  

H22=EH2[[1,2]];  

"simulate fgn";  

SimulateFGN[H_,n_]:=Module[{N,ac}, N =2^Ceiling[Log[2,n-1]];  

ac=Table[FGNAcf[k,H],{k,0, N }];  

Take[SimulateGLP[ac,n]];SimulateGLP[y_]:=Module[{m=Length[y],n,c,g,Z,  

Ncap},n=2^Ceiling[Log[2,m-1]];acvf=If[n==m-  

1,y,PadRight[y,n+1]];Ncap=2*n;  

c=Join[acvf,Rest[Reverse[Rest[acvf]]]];  

g=Re[Fourier[c,FourierParameters->{1,-1}]];  

Z=RandomVariate[NormalDistribution[0,1],Ncap-2];  

Z=(Complex[Sequence@@#1]&)/@Partition[Z,2];  

Z=Flatten[{RandomVariate[NormalDistribution[0,Sqrt[2]]],Z,RandomVariate  

[NormalDistribution[0,Sqrt[2]]],Reverse[Conjugate[Z]]}];  

Take[Re[InverseFourier[Sqrt[g]*Z,FourierParameters->{0,-1}]],m]/Sqrt[2]];  

FGNAcf[k_,H_]:=Module[{},0.5*(Abs[k+1.0]^(2.0*H)-  

2*Abs[k]^(2.0*H)+Abs[k-1.0]^(2.0*H))];  

"fgn at H=.65 and n=20";  

SmH111=SimulateFGN[H11,110];  

"fgn at H=.9 and n=20";  

SmH222=SimulateFGN[H22,110];  

Do[  

sumαα=0;  

sumββ=0;  

sumμμ=0;  

summm=0;  

w[j_]:=j+10(j-1);  

SmH11[j_]:=Table[SmH111[[i]],[i,w[j],w[j]+10]];  

SmH22[j_]:=Table[SmH222[[i]],[i,w[j],w[j]+10]];  

SmH1=SmH11[j];  

SmH2=SmH22[j];  

n=2;  

While[n<=NN,

```

```

Clear[\[alpha]1,m1,\[beta]1,\[mu]1];
Yk11[n_]:= \[Sigma]_{i=0}^{\infty}((1 - \alpha1 \Delta t)^i(\alpha1 m1 \Delta t + \beta1 SmH2[[Abs[i + 1]]]);
Xk1[n_]:=1+\[mu]1 \Delta t+SmH1[[n]]*
\Sigma_{i=0}^{\infty}((1 - \alpha1 \Delta t)^i(\alpha1 m1 \Delta t + \beta1 SmH2[[Abs[i + 1]]]) ;
Yk[n_]:= \[Sigma]_{i=0}^{\infty}(1 - \alpha \Delta t)^i(\alpha m \Delta t + \beta SmH2[[Abs[i + 1]]]);
Xk[n_]:=1+\mu \Delta t+Yk[n]*SmH1[[n]];
mu[n_]:=Mean[Table[Xk1[i],{i,1,n}]];
X[n_]:=Table[Xk1[i],{i,1,n}]; XX[n_]:=Table[Xk[i],{i,1,n-
1}]~Join~{Xk1[n]};
\gamma\xi[n_]:=1/2 (Abs[(n-1) \Delta t]^2 H11+Abs[(n+1) \Delta t]^2 H11-2 Abs[n \Delta t]^2 H11);
\gamma\eta[n_]:=1/2 (Abs[(n-1) \Delta t]^2 H22+Abs[(n+1) \Delta t]^2 H22-2 Abs[n \Delta t]^2 H22);
\gamma X[n_]:=Yk[n]^2 \gamma\xi[n];
\gamma Y[n_]:= \beta^2 \Sigma_{i=0}^{\infty} \Sigma_{j=0}^{\infty} (1 - \alpha \Delta t)^{i+j} \gamma\eta[n + 1 - j];

\Gamma n1[n_]:=Table[\gamma X[i-j],{i,1,n-1},{j,1,n-1}];"\Gamma n-1";
\gamma n1[n_]:=Table[\gamma X[n-i],{i,1,n-1},{j,1,1}];"\gamma n-1";
\gamma Tn1[n_]:=Transpose[\gamma n1[n]];"\gamma n-1 transpose";
\gamma X0=\gamma X[0];"\gamma X(0)";
\Gamma[n_]:=ArrayFlatten[\{\{\Gamma n1[n],\gamma n1[n]\},\{\gamma Tn1[n],\gamma X0\}\}];
inv\Gamma[n_]:=Inverse[\Gamma[n]];
\gamma[n_]:=Table[\{\gamma X[i]\},{i,1,n}];"\gamma T in 3.27";
VT2[n_]:=Abs[\gamma X[0]-Transpose[\gamma[n]].inv\Gamma[n].\gamma[n]];"\gamma T in 3.27";
VT22[n_]:=ToExpression[StringReplace[ToString[VT2[n]],{\">>\"}]];
inv\Gamma[1]=1/\gamma X0;
For[i=1,i<=n,i++,
\phi[i_]:=inv\Gamma[i].\gamma[i];
\phi1[i_]:=Flatten[\phi[i]];
For[j=1,j<=n,j++,
If[i==j,a[i,j]=1];
If[i<j,a[i,j]=0];
If[i>j,a[i,j]=-\phi1[i-1][j]];
];
a[1,1]=1;
a[2,1]=-\gamma X[1]/\gamma X0;

```

```

];
A=Table[a[i,j],{i,1,n},{j,1,n}];
For[i=2,i<=n,i++,
For[j=2,j<=n,j++,
VT1=Abs[γX0-γX[1]* 1/γX0 *γX[1]];
d[1,1]=(1/VT1);
If[i==j,d[i,j]=1/VT22[i]];
If[i<j,d[i,j]=0];
If[i>j,d[i,j]=0];
]
];
KK=Table[If[i==1,d[i,j]=0,d[i,j]],{i,1,n},
{j,1,n}];
KK=Table[If[j==1,d[i,j]=0,d[i,j]],{i,1,n},
{j,1,n}];
d[1,1]=Abs[1/VT1];
KK=Table[d[i,j],{i,1,n},{j,1,n}];
segmainv[n_]:=SetPrecision[Transpose[A].KK.A ,5];
“segma[n_]:=PaddedForm[SetPrecision[Inverse[segmainv[n]],5],{5,5}]”;
DetKKK[n_]:=VT1 * $\prod_{i=1}^L$  VT2[i];
“define penalty function “;
g1[n_]:=-γX[n];
g2[n_]:= -  $\sum_{i=1}^L$  ( $\mathbf{1} - \alpha \Delta t$ )i ( $\alpha m \Delta t$ )2  $\Delta t^{2H_{11}} - \sum_{i=1}^L$  ( $\mathbf{1} - \alpha \Delta t$ )2i  $\beta^2 \Delta t^{2(H_{22}+H_{11})}$ ;
G1[n_]:=Piecewise[{ {g1[n],g1[n]>ε}, {(g1[n]-ε)^2/(4 ε),-ε<g1[n]<ε},{0,g1[n]<-ε}}];”3.36 w.r.t g1”;
G2[n_]:=Piecewise[{ {g2[n],g2[n]>ε}, {(g2[n]-ε)^2/(4 ε),-ε<g2[n]<ε},{0,g2[n]<-ε}}];”3.36w.r.t g2”;
;n++];
“lhood[NN_]:=Log[PDF[MultinormalDistribution[Flatten[Table[mu[i],{i,1,N
N}]],segma[NN]],X[NN]]]”;
lhood1[NN_]:=Log[Exp[-0.5* Transpose[Table[Xk1[i]-
mu[i],{i,1,NN}],{1}].segmainv[NN].Table[Xk1[i]-

```

```

mu[i],{i,1,NN}]]/ToExpression[StringReplace[ToString[(2 Pi)  $\frac{\text{NN}}{2}$ 
DetKKK [NN] $\frac{1}{2}$  ], {"{"->"""", "}"->"""}]]];
op=NMinimize[-lhood1[NN]- $\epsilon/4 \sum_{i=1}^{NN} G1[i] -\epsilon/4 \sum_{i=1}^{NN} G2[i]$ 
,{ $\alpha_1, m_1, \beta_1, \mu_1$ },WorkingPrecision->15,Method->"DifferentialEvolution"];
dd=op;
answer=op[[1]];
optimallu=u+1=answer;
var=dd[[2]]; "the answer";

 $\alpha\alpha$ =var[[1]];
 $\alpha\alpha\alpha$ = $\alpha\alpha$ [[2]];
suma $\alpha$ =suma $\alpha$ + $\alpha\alpha\alpha$ ;
suma $\alpha\alpha$ =suma $\alpha$ ;

mm=var[[2]];
mmm=mm[[2]];
summ=summm+mmm;
summm=summ;

 $\beta\beta$ =var[[3]];
 $\beta\beta\beta$ = $\beta\beta$ [[2]];
sum $\beta$ =sum $\beta\beta$ + $\beta\beta\beta$ ;
sum $\beta\beta$ =sum $\beta$ ;

 $\mu\mu 0$ =var[[4]];
 $\mu\mu\mu$ = $\mu\mu 0$ [[2]];
sum $\mu$ =sum $\mu\mu$ + $\mu\mu\mu$ ;
sum $\mu\mu$ =sum $\mu$ ;

"Print[dd];";
sepvar=Table[var[[i,2]],{i,1,4}];
{ $\alpha_1, m_1, \beta_1, \mu_1$ } = sepvar;
Clear[ $\alpha_1, m_1, \beta_1, \mu_1$ ];
,{j,JJ}]];
Table[optimalli,{i,1,JJ}];

```

```

H1hut=H11;
H1huttl=l+1=H1hut;
H2hut=H22;
H2huttt=t+1=H2hut;
ahut=sumaa/JJ;
ahuttv=v+1=ahut;
mhut=summm/JJ;
mhuttc=c+1=mhut;
βhut=sumββ/JJ;
βhutte=e+1=βhut;
μhut=sumμμ/JJ;
μhuttf=f+1=μhut;
Print[H1hut];
Print[H2hut];
Print[ahut];
Print[mhut];
Print[βhut];
Print[μhut];
Print[">>>>>>>>>>>>>>>>>>>"];
];
H1est=Table [H1hutti,{i,1,RR }];
H2est=Table [H2hutti,{i,1,RR }];
αest=Table[ahutti,{i,1,RR }];
mest=Table[mhutti,{i,1,RR }];
βest=Table[βhutti,{i,1,RR }];
μest=Table[μhutti,{i,1,RR }];
H1hutav=Mean[H1est];
H2hutav=Mean[H2est];
ahutav=Mean[αest];
mhutav=Mean[mest];
βhutav=Mean[βest];
μhutav=Mean[μest];
“αvar=Variance[αest];
mvar=Variance[mest];
βvar=Variance[βest];
μvar=Variance[μest]”;

```

```

Print["H1hut-average = ", H1hutav];
Print["H2hut-average = ", H2hutav];
Print["αhut-average = ", αhutav];
Print["mhut-average = ", mhutav];
Print["βhut-average = ", βhutav];
Print["μhut-average = ", μhutav];
Print["H1-variance = ", Variance[H1est]];
Print["H2-variance = ", Variance[H2est]];
Print["α-variance = ", Variance[αest]];
Print["m-variance = ", Variance[mest]];
Print["β-variance = ", Variance[βest]];
Print["μ-variance = ", Variance[μest]];
Print["H1-bias = ", Abs[H1 - H1hutav]];
Print["H2-bias = ", Abs[H2 - H1hutav]];
Print["α-bias = ", Abs[α - αhutav]];
Print["m-bias = ", Abs[m - mhutav]];
Print["β-bias = ", Abs[β - βhutav]];
Print["μ-bias = ", Abs[μ - μhutav]];
Print["H1-MSE = ", Variance[H1est] + (Abs[H1 - H1hutav])^2];
Print["H2-MSE = ", Variance[H2est] + (Abs[H2 - H2hutav])^2];
Print["α-MSE = ", Variance[αest] + (Abs[α - αhutav])^2];
Print["m-MSE = ", Variance[mest] + (Abs[m - mhutav])^2];
Print["β-MSE = ", Variance[βest] + (Abs[β - βhutav])^2];
Print["μ-MSE = ", Variance[μest] + (Abs[μ - μhutav])^2];

```