

International Journal of Applied Mathematics and Statistics™

ISSN: 0973-7545 (Online), ISSN 0973-1377 (Print)

www.ceser.in/ceserp/
www.ceserp.com/cp-jour/

International Journal of Applied Mathematics and Statistics™

The main aim of the **International Journal of Applied Mathematics and Statistics™** [ISSN 0973-1377 (Print); 0973-7545 (Online)] is to publish refereed, well-written original research articles, and studies that describe the latest research and developments in the area of applied mathematics and statistics. This is a broad-based journal covering all branches of mathematics, statistics and interdisciplinary research. **International Journal of Applied Mathematics and Statistics (IJAMAS)** is a peer-reviewed journal and published by **CESER Publications**.

Reviewed, Abstracted and Indexed: The **IJAMAS** is reviewed, abstracted and indexed by the **Mathematical Reviews**; **MathSciNet**; **Zentralblatt für Mathematik (Zentralblatt MATH)**; **ERA: Excellence in Research for Australia (by Govt. of Australia)**; **Statistical Theory and Method Abstracts (STMA-Z)**, **Current Index to Statistics (CIS)** [The Current Index to Statistics (CIS) is a joint venture of the *American Statistical Association & Institute of Mathematical Statistics, USA*], **International Abstracts in Operations Research (IAOR)**, **Indian Science Abstracts**; **Academic keys**; **JournalSeek**, **Ulrich's Periodicals Directory**, **International Statistical Institute (ISI, Netherlands) Journal Index**, **IndexCopernicus**, **Getcited...**



ISSN 0973-1377 (Print)
ISSN 0973-7545 (Online)

Journal Contact

Mailing Address

CESER Publications,
Post Box No. 113,
Roorkee-247667
INDIA

Principal Contact

Dr. Kaushal K. Srivastava
Managing Editor, IJAMAS

CESER Publications,
Post Box No. 113,
Roorkee-247667, INDIA

Email: eic.ijamas@yahoo.com

Support Contact

P & S Editor, CESER Publications
Email: ceser_info@yahoo.com

International Journal of Applied Mathematics and Statistics™

ISSN: 0973-7545 (Online), ISSN 0973-1377 (Print)

www.ceser.in/ceserp/
www.ceserp.com/cp-jour/

Editorial Board

Editors-in-Chief:

R. K. S. Rathore, Department of Mathematics, Indian Institute of Technology, Kanpur, INDIA.

Akca Haydar, Abu Dhabi University, Department of Mathematics, UAE.

Chunhui Lai, School of Mathematics and Statistics, Minnan Normal University, Zhangzhou, Fujian, China

Delfim F. M. Torres, Department of Mathematics, University of Aveiro, Portugal

Martin Bohner, Department of Mathematics, University of Missouri-Rolla, USA

Editors:

Alain S. Togbe, Purdue University North Central, USA

Alex Maritz, Swinburne University of Technology, Australia

Alexander Grigorash, University of Ulster, U.K.

Alina Barbulescu, Ovidius University of Constantza, Romania

Nahit Ann Galstyan, University of Texas-Pan American, USA

Andrei Volodin, University of Regina Regina, Saskatchewan, Canada.

Alexandru Murgu, University of Cape Town, South Africa

Anna Karczewska, University of Zielona Gora, Poland

Ahmad Erfanian, Ferdowsi University of Masshad, Iran

Ashwin Vaidya, University of North Carolina - Chapel Hill, USA

Arsham Borumand Saeid, Shahid Bahonar university of Kerman, Iran

Ayşe Altın, Hacettepe University, Turkey

Bixiang Wang, New Mexico Institute of Mining & Technology, USA

Bogdan G. Nita, Montclair State University, USA

Chieh-Jen Shieh, Chang Jung Christian University, Tainan, Taiwan

Christos Koukouvinos, National Technical University of Athens, Athens, Greece

Defa Hu, School of Information, Hunan University of Commerce, Changsha, China

Diego Ernesto Dominici, State University of New York at New Paltz, USA

Doreen De Leon, California State University, USA

Dudek Wiesław A., Wrocław University of Technology, Poland

Eduardo V. Teixeira, Rutgers University, USA

Edward Neuman, Southern Illinois University, USA

En-Bing Lin, Central Michigan University, USA

International Journal of Applied Mathematics and Statistics™

ISSN: 0973-7545 (Online), ISSN 0973-1377 (Print)

www.ceser.in/ceserp/
www.ceserp.com/cp-jour/

Editors:

Ferhan Atici, Western Kentucky University, USA
Fernando Manuel Lucas Carapau, University of Evora, Portugal
Filia Vonta, National Technical University of Athens, Athens, Greece
Florentin Smarandache, University of New Mexico, USA
Ganatsiou V. Chrysoula, University of Thessaly, Greece
Guo Wei, University of North Carolina at Pembroke, USA
Gyula Y. Katona, Budapest University of Technology and Economics, Hungary
H. M. Srivastava, University of Victoria, Victoria, British Columbia, Canada
Henryk Fuks, Department of Mathematics, Brock University, St. Catharines, Canada
Hong-Jian Lai, Department of Mathematics, West Virginia University, Morgantown, USA
Irene Sciriha, University of Malta, Malta
Jianfeng Hou, Fuzhou University, Fuzhou, Fujian, China
Jose Almer T. Sanqui, Appalachian State University, USA
Jyh-Rong Chou, I-Shou University, Kaohsiung, Taiwan
Kalliopi Mylona, National Technical University of Athens, Athens, Greece
Karen Yagdjian, University of Texas-Pan American, USA
Kewen Zhao, University of Qiongzhou, Hainan, China
Ki-Bong Nam, University of Wisconsin Whitewater, USA
Loubes Jean-MicheUniversite Paul Sabatier, France
Michael D. Wills, Weber State University, USA
Ming Fang, Norfolk State University, USA
Miranda I. Teboh-Ewungkem, Lehigh University, USA
Muharem Avdispahic, University of Sarajevo, Bosnia
Mustafa Bayram, Yildiz Teknik Universitesi, Turkey
Nor Haniza Sarmin, Universiti Teknologi, Malaysia
Nor'aini Aris, Universiti Teknologi, Malaysia
Nihal Yilmaz Ozgur, Balikesir University, Turkey
Oliver Jones, California State University, USA
Omar Mohd Rijal, University Malaya, Malaysia
Piotr Matus, Institute of Mathematics of NASB, Belarus
Răzvan Răducanu, Al. I. Cuza University, Romania
Ricardo Lopez-Ruiz, Universidad de Zaragoza, Spain
Ridong Hu, Huaqiao University, Quanzhou City, China
Rui Xu, University of West Georgia, USA
Ruqiang Yan, National Institute of Standards and Technology, USA
Shang-Pao Yeh, I-Shou University, Kaohsiung, Taiwan
Samir H. Saker, Mansoura University, Egypt
Shamsuddin Ahmad, Universiti Teknologi, Malaysia
Sheng-Wen Hsieh, Far East University, Tainan, Taiwan
Somesh Kumar, Indian Institute of Technology, Kharagpur, India
Song Wang, University of Western Australia, Australia
Sukanto Bhattacharya, Alaska Pacific University, USA
Weijiu Liu, University of Central Arkansas, USA
Wenjun Liu, Nanjing University of Information Science and Technology, Nanjing, China
Wen-Xiu Ma, University of South Florida, USA
Xiaofeng Gu, Texas State University, San Marcos, USA
Xiaoli Li, University of Birmingham, UK
Xiao-Xiong Gan, Morgan State University, USA

International Journal of Applied Mathematics and Statistics™

ISSN: 0973-7545 (Online), ISSN 0973-1377 (Print)

www.ceser.in/ceserp/
www.ceserp.com/cp-jour/

2015, Volume 53, Issue Number: 5



 Open Access  Subscription or Fee Access

Table of Contents

Articles

An Alternative Bayesian Estimator of Small Proportion Using Binomial Group Testing	PDF 
<i>K. Huang, J. Mi</i>	1-15
Spatio-Temporal Analysis of Inflation Rate in East Java, Indonesia :Vector Autoregressive Approach	PDF 
<i>E. Sumarminingsih</i>	16-23
MCMC-Based Bayesian Estimation for Next Fault Time of Software Via NHPP and Generalized Exponential Distribution	PDF 
<i>M. S. Aminzadeh</i>	24-32
Alternative of Strict Avalanche Criterion Test on Block Cipher Using Fisher's Method	PDF 
<i>A. A. Lestari, A. Kurnia, F. M. Afendi</i>	33-39
Reduced Support Vector Machine Based on Nonhierarchical Clustering Techniques for Classifying Mixed Large-Scale Datasets	PDF 
<i>S. Andari, S.W. Purnami</i>	40-46
The Computation of the Abelianization of All Bieberbach Groups of Dimension Five with Symmetric Point Group of Order Six	PDF 
<i>Y. T. Tan, R. Masri, N. Mohd Idrus, W. N. F. Wan Mohd Fauzi, N. H. Sarmin, H. I. Mat Hassim</i>	47-52
Comparing PLS-SEM and SEM Bayesian for Small Sample in TAM Analysis	PDF 
<i>M. A. Anggorowati</i>	53-58
Comparing Quasi Newton BFGS and Nelder Mead Algorithm for Box-Cox Transformation	PDF 
<i>W. P. Saputra, M. A. Anggorowati</i>	59-66
The Effect of Adding FFST on Secondary Flow Characteristics Near Endwall of Asymmetry Airfoil (Case Study of different camber)	PDF 
<i>Heru Mirmanto, Herman Sasongko, Iis Rohmawati, Ika Nurjannah</i>	67-72
A Homological Functor of the Second Bieberbach Group with Dihedral Point Group	PDF 
<i>W. N. F. Wan Mohd Fauzi, N. Mohd Idrus, R. Masri, Y. T. Tan, N. H. Sarmin, H. I. Mat Hassim</i>	73-76
Forecasting Electricity Demands in Java-Bali Region using Flexible Forecasting Approach	PDF 
<i>H. Kuswanto, M. Salamah, F.A. Kusumawati</i>	77-85
Forecasting Long Memory Time Series for Stock Price with Autoregressive Fractionally Integrated Moving Average	PDF 
<i>Dodi Devianto, Maiyastri, Septri Damayanti</i>	86-95
Optimization of Economic Dispatch Using Bacterial Foraging Optimization Algorithm	PDF 
<i>S. Komsiyah, D. Suhartono, M. Astriyanti</i>	96-102
Forecasting the Probability of Default of PN17 Company using KMV-Merton Model	PDF 
<i>M. Y. Norliza, M. J. Maheeran</i>	103-108
Cox Proportional Hazard with Multivariate Adaptive Regression Splines to Analyze the Product Sales Time in E-Commerce	PDF 
<i>E. Irvansyah, D. A. N. O. Stefani, R. D. Bekti</i>	109-115
Hierarchical Forecasting Method Based on ARIMAX and Recurrent Neural Network for Motorcycle Sales Prediction	PDF 
<i>I. G. S. A. Prayoga, Suhartono, S.P. Rahayu</i>	116-124
Intervention Model Indonesia's Inflation Due to Rising Fuel Prices	PDF 
<i>S. Rahardiantoro, R. Budiarti, B. Sartono</i>	125-129
Spatial Simultaneous Equation Model: Case Study Empirical Analysis of Regional Economic Growth in Central Java Province	PDF 
<i>Setiawan, I.S. Ahmad, Sutikno</i>	130-139
Application Of Fuzzy Analytical Hierarchy Process and Fuzzy Multiobjective Linear Programming For Selection and Evaluation Of Suppliers	PDF 
<i>S. Komsiyah</i>	140-145
Can Gold Be Used As a Hedge or Safe Haven for Equity and Exchange Rate?	PDF 
<i>N. S. Zainal Abidin, A. H. Nawawi, S. A. Sheikh Hussin, M. A. Mohd</i>	146-152
Modeling Flood and Other Factors Effects on Demand Currency (Outflow) in Jakarta Using Autoregressive Distributed Lag (ARDL)	PDF 
<i>Dwi Endah Kusriani, Suhartono, Rosyid Abdullah, Mukhtasar</i>	153-162
D-Optimal Designs for Morgan Mercer Flodin (MMF) Models Without Intercept	PDF 
<i>Tatik Widiharih, Sri Haryatmi, Gunardi</i>	163-171
A Comparison Study of Parametric and Semiparametric Bootstrapping in Deterministic Simulation	PDF 
<i>Elmanani Simamora, Subanar, Sri Haryatmi Kartiko</i>	172-181
Finding Minimum Centered L2 Discrepancy Values to Construct Uniform Design Tables in GLP Method with Generating Vector	PDF 
<i>Anwar Fitrianto, Grace Lau ChuiTing, Leong Wah June, Habshah Midi</i>	182-186
An Alternative Identification of Influential points in Cox Proportional Hazards Model	PDF 
<i>Rebecca Loo Ting Jiin, Anwar Fitrianto, Sohel Rana, Habshah Midi</i>	187-191
Robust feasible generalized least squares: A remedial measures of heteroscedasticity	PDF 
<i>Sohel Rana, Anwar Fitrianto, Khor Wen Jie, Habshah Midi, A.H.M.R. Imon</i>	192-199
Value-at-Risk and Expected Shortfall Relationship	PDF 
<i>Aniq A. Rohmawati, Khreshna I. A. Syuhada</i>	200-205
Estimating the Parameter of Dynamic Panel Data Model Using Arellano-Bond Method	PDF 
<i>Widya Irmaningtyas, Dedi Rosadi</i>	206-211
A Gompertz model of the Strategy Inventory for Language Learning questionnaire	PDF 
<i>J.J. Kiram, J. Sulaiman, S. Swanto, W. A. Din</i>	212-219

Forecasting Long Memory Time Series for Stock Price with Autoregressive Fractionally Integrated Moving Average

Dodi Devianto¹, Maiyastri² and Septri Damayanti³

^{1,2,3}Department of Mathematics, Faculty of Mathematics and Natural Sciences,
Andalas University, Limau Manis Campus, Padang 25163, INDONESIA;
Email: ¹ddevianto@fmipa.unand.ac.id; ²maiyastri@gmail.com; ³septridamayanti@yahoo.com

ABSTRACT

The presence of long memory time series is characterized by autocorrelation function which decrease slowly or hyperbolic. The best suited model for this time series phenomenon is Autoregressive Fractionally Integrated Moving Average (ARFIMA) that can be used to model historical stock price in financial data analysis. This research is aimed to assess the ARFIMA modeling on long memory process with parameter estimation method of Geweke and Porter Hudak (GPH), and applied to opening price of Kedaung Indah Can Tbk Stock from May 2nd 2005 until March 26th 2012. The best suited model is found ARFIMA(5,0.452,4) where for short time forecasting is shown very close to actual stock price with small standard error.

Keywords: Long memory process, autoregressive fractionally integrated moving average, stock price, Geweke and Porter Hudak method.

Mathematics Subject Classification: 62M10, 91B84

Computing Classification System: I.6.3

1. INTRODUCTION

The concept of long memory process has developed and gave its substantial evidence to describe the phenomenon in time series such as data behavior in financial and macroeconomics. The presence of long memory can be defined from an empirical approach in terms of the persistence autocorrelations between observed time series data. The extent of the persistence is detected by data stationary along the process, that is characterized by autocorrelations which decrease slowly or hyperbolic associated with class of autoregressive moving average.

The most noted definition of long memory process has been given by Haslet and Raftery (1989), they said that the data are categorized as long memory is marked with autocorrelations function plot does not fall exponentially but decrease slowly or hyperbolic. The phenomenon of this long memory in time series was introduced by Hurst (1951) in different data sets. Granger and Joyeux (1980) and Hosking (1981), developed a model suited for long memory process that is Autoregressive Fractionally

Integrated Moving Average (ARFIMA), where the best model explained time series in the form of short memory and long memory with differencing parameter as a real numbers.

The study of long memory process, particularly regarding to ARFIMA model is developed in many data analysis over both time and space, and one of its most attraction is suited to long run predictions and effects of shocks to conventional macroeconomic approach. Therefore, in this study it will be shown long memory process using ARFIMA models with differencing parameter estimation method by Geweke and Porter Hudak (GPH) to historical data from the opening price Kedaung Indah Can Tbk stock. The used of ARFIMA model in this study because it can estimate differencing parameter directly and it is not necessary at the beginning to know the value of the order from autoregressive and moving average.

2. LONG MEMORY PROCESS AND AUTOREGRESSIVE FRACTIONALLY INTEGRATED MOVING AVERAGE

There are several possible definitions of long memory process and its properties. According to Palma (2007), let $\gamma(h) = Cov(X_t, X_{t+h})$ be the Autocovariance Function (ACVF) at lag h of the stationary process $\{X_t : t \in \mathbb{Z}\}$ where X_t is data at time t . The long memory process is presence if satisfy

$$\sum_{h=-\infty}^{\infty} |\gamma(h)| = \infty.$$

Furthermore, Wei (1990) has explained that a process $\{Z_t\}$ where Z_t satisfy difference equations $\nabla^d X_t = Z_t$ is called white noise if it is a sequence of uncorrelated random variables from a fixed distribution with mean zero, and variance σ^2 and $\gamma_h = Cov(Z_t, Z_{t+h}) = 0$ for all $h \neq 0$.

Long memory model is divided into short memory and long memory process by using ARFIMA model. In the following Brockwell and Davis (1991) give some important definition related to ARFIMA model.

Definition 1. The process $\{X_t, t = 0, \pm 1, \dots\}$ is said to be an ARFIMA(0,d,0) process with $d \in (-1/2, 1/2)$ if $\{X_t\}$ is a stationary solution with mean zero with the difference equations

$$\nabla^d X_t = Z_t$$

where $\{Z_t\}$ is white noise. The process $\{X_t\}$ is often called fractionally integrated noise.

Definition 2. The process $\{X_t, t = 0, \pm 1, \dots\}$ is said to be an ARFIMA(p,d,q) process with $d \in (-1/2, 1/2)$ or a fractionally integrated ARMA(p,q) process if $\{X_t\}$ is stationary and satisfies the difference equations

$$\phi_p(B)\nabla^d X_t = \theta_q(B)Z_t,$$

where $\{Z_t\}$ is white noise, fractional difference operator $\nabla^d = (1-B)^d$, and ϕ, θ are polynomials degrees of p and q respectively.

Hosking (1980) has explained that the fractional difference operator on the ARFIMA(p,d,q) model is an expansion of the binomial

$$\nabla^d = (1-B)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j B^j,$$

where

$$\binom{d}{j} = \frac{d!}{j!(d-j)!} = \frac{\Gamma(d+1)}{\Gamma(j+1)\Gamma(d-j+1)},$$

B is the backward shift operator, and $\Gamma(X)$ is the gamma function, so that

$$\nabla^d = \binom{d}{0} (-1)^0 B^0 + \binom{d}{1} (-1)^1 B^1 + \binom{d}{2} (-1)^2 B^2 + \dots = 1 - dB - \frac{1}{2}(1-d)dB^2 - \frac{1}{6}(1-d)(2-d)dB^3 + \dots$$

Spectral density is a positive real function of the frequency variable associated with a deterministic function of time. Palma (2007) has explained spectral density as follows

$$f(\lambda) = f_0(\lambda) \left[2 \sin \frac{\lambda}{2} \right]^{-2d} = \frac{\sigma^2}{2\pi} \left| \frac{\theta(e^{-i\lambda})}{\phi(e^{-i\lambda})} \right|^2 \left[2 \sin \frac{\lambda}{2} \right]^{-2d},$$

with $f_0(\lambda) = (\sigma^2/2\pi) |\theta(e^{-i\lambda})/\phi(e^{-i\lambda})|^2$ is the spectral density of ARMA(p,q) and λ is the frequency of the periodogram.

The value of ACVF from ARFIMA($0,d,0$) model is given by

$$\gamma_0(h) = \sigma^2 \frac{\Gamma(1-2d)}{\Gamma(1-d)} \frac{\Gamma(h+d)}{\Gamma(1+h-d)},$$

where $\Gamma(\cdot)$ is the gamma function, h is lag, n is the number of observations. Autocorrelation Function (ACF) is a correlation of time series between $\{X_t\}$ and $\{X_{t+h}\}$. The equation of ACF can be written as follows

$$\rho_0(h) = \frac{\Gamma(1-d)}{\Gamma(d)} \frac{\Gamma(h+d)}{\Gamma(1+h-d)}.$$

The Partial Autocorrelation Function (PACF) is a correlation between $\{X_t\}$ and $\{X_{t+h}\}$ if there are time lag influence from 1, 2, 3, ..., $h-1$. The PACF was as follows

$$\phi_{nn} = \frac{d}{(n-d)},$$

and $\phi_{nn} \approx (d/n)$ for large n .

According to Boutahar and Khalfaoui (2011), and Hosking (1981), the main characteristics of an ARFIMA(p,d,q) model as follows

1. If $d > -1/2$, then X_t is invertible.
2. If $d < 1/2$, then X_t is stationary.
3. If $-1/2 < d < 0$, then ACF $\rho(h)$ decreases more quickly than the case $0 < d < 1/2$, this model is called short memory.
4. If $0 < d < 1/2$, then X_t is a stationary long memory model which is the ACF decays hyperbolically to zero.
5. If $d = 1/2$, then spectral density is unbounded at zero frequency.

The reason for choosing this family of ARFIMA(p,d,q) process for modeling purposes is therefore obvious from characteristic differencing parameter d . The effect of the d parameter on distant observation decays hyperbolically as the lag increases, while the effects of the ϕ and θ parameters decay exponentially. Thus d may be chosen to describe the high lag correlation structure of a time series while the ϕ and θ parameters are chosen to describe the low lag correlation structure. Indeed the long term behavior of an ARFIMA(p,d,q) process may be expected to be similar to that of an ARIMA(p,d,q) process with the same value of d , since for very distant observations the effects of the the ϕ and θ parameters will be negligible.

3. EMPIRICAL RESULT

This section is to give emperical result of data analysis to describe ARFIMA model. The best suited ARFIMA model for historical stock price is using to forecast long run prediction.

3.1. Data and Methods

We perform the analysis of long memory process from Kedaung Indah Can Tbk stock in the period May 2nd 2005 until March 26th 2012 during 344 weeks. This historical stock prices data is used to obtain time series model and its forecasting. The analysis follows these steps:

1. Model Identification

Identification of patterns for time series is using plot of ACF and PACF, and then using Augmented Dickey Fuller (ADF) test to identifying its stationarity. In the case of mean is not stationary, it is used differencing with parameter d , for the short memory process differencing d as an integer number, while for long memory process, carried out with differencing d as a real number is located at $0 < d < 1/2$.

2. Parameter Estimation

One of the differencing parameter estimation method is using GPH. This estimator suggests that the parameter d , which is also called the long memory parameter, can be consistently estimated from

least squares regression, that is obtained from a logarithmic regression of spectral density. Estimation of long memory parameter d , denoted by \hat{d}_{GPH} , is defined as follows

$$\hat{d}_{GPH} = -\frac{\sum_{j=1}^m (x_j - \bar{x}_j)(y_j - \bar{y}_j)}{\sum_{j=1}^m (x_j - \bar{x}_j)^2},$$

where $m = n^{H/2}$ is number of fourier frequencies for n observations, x_j is j th data observation and y_j is j th variable for spectral density.

3. Diagnostic Checking

After going through the parameter estimation steps, the next steps in the testing of ARFIMA modeling is residuals, whether they are independent, have zero mean and constant variance. This assumption is tested by Ljung-Box test (see Wei, 1990). In addition, the residual must satisfy the assumption of normal distribution, because the parameter p and q in ARFIMA are estimated using maximum likelihood. To test whether the residuals are normally, can be done using Kolmogorov Smirnov test.

4. Forecasting

The next steps in the analysis of time series is a forecasting. Bisaglia (2002) has explained that there are some criteria within selection of model.

(i) Akaike Information Criterion (AIC).

The model selected is a model with the lowest AIC value. The equation is used to count the AIC value is

$$AIC = n \ln(\hat{\sigma}_n^2) + 2(p + q + 1).$$

(ii) Akaike Information Criterion with Correction (AICC).

The model with the lowest AICC value is selected, were AICC equation as follow

$$AICC = n \ln(\hat{\sigma}_n^2) + \frac{2n(p + q + 1)}{(n - p - q - 2)}.$$

(iii) Bayesian Information Criterion (BIC).

The model selected is a model with the lowest BIC value. The equation of BIC as follow

$$BIC = n \ln(\hat{\sigma}_n^2) + (p + q + 1) \log n$$

where $\hat{\sigma}_n^2$ is variance of white noise model, and n is number of observations.

According to Brockwell and Davis (1991), the best linear estimation of X_{t+h} is \tilde{X}_{t+h} . Assume that the model of causality and invertibility, so then it is obtained time series forecasting as follows

$$\tilde{X}_{t+1} = -\sum_{j=1}^t \pi_j X_{t+1-j}, \quad \tilde{X}_{t+2} = -\pi_1 \tilde{X}_{t+1} - \sum_{j=2}^{t+1} \pi_j X_{t+2-j}, \dots$$

where π is parameter for times series model.

3.2. Model Identification

The first step to make model identification is by using time series plot. The plot of opening price data from Kedaung Indah Can Tbk stock price are presented in the following figure

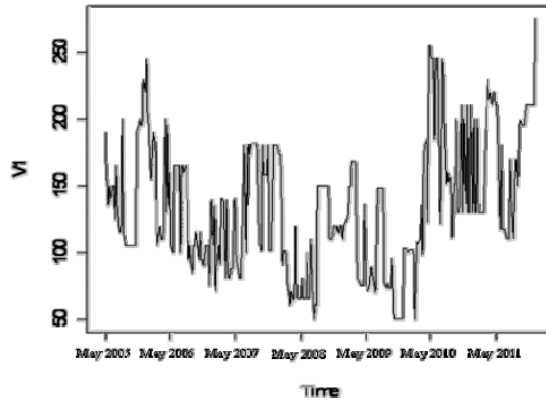


Figure 1. Opening Price Data of Kedaung Indah Can Tbk.

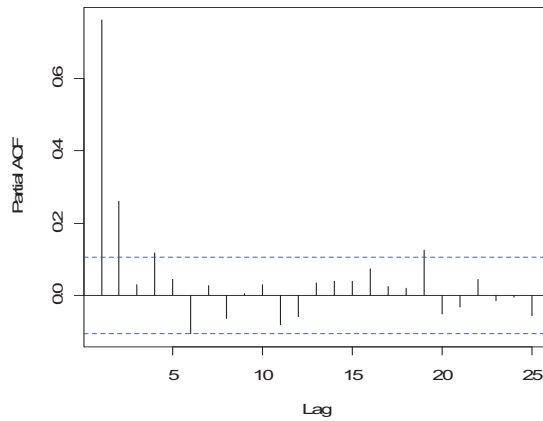


Figure 2. ACF of Opening Price Kedaung Indah Can Tbk Stock Before Differencing.

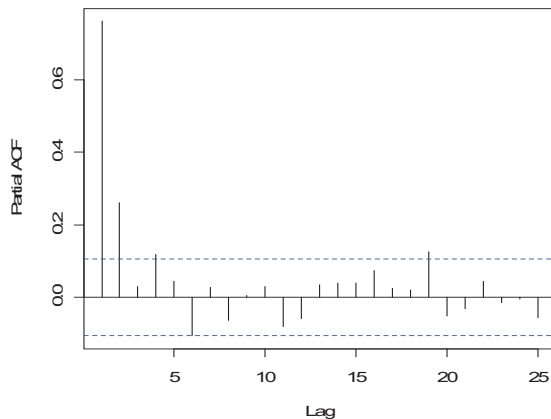


Figure 3. PACF of Opening Price Kedaung Indah Can Tbk Stock Before Differencing.

Based on Figure 1, it can be seen that the time series is not spread fairly stationary. Therefore, it needs to do differencing. In addition, it is also examined the ACF and PACF to identify with certainty the stationary property. Figure 2 shows autocorrelation of each lag hyperbolic decreased slowly towards zero, while Figure 3 shows cut lag after lag p . This indicates stationarity and long memory process, to solve this problem, the suited model which can be used is ARFIMA(p,d,q) model, where d is long memory parameter.

3.3. Parameter Estimation

Differencing parameter d is estimated by using GPH method on opening price data from Kedaung Indah Can Tbk stock, by developing macro on MATLAB 5.3 program, it is obtained a value of long memory parameter d is 0.452.

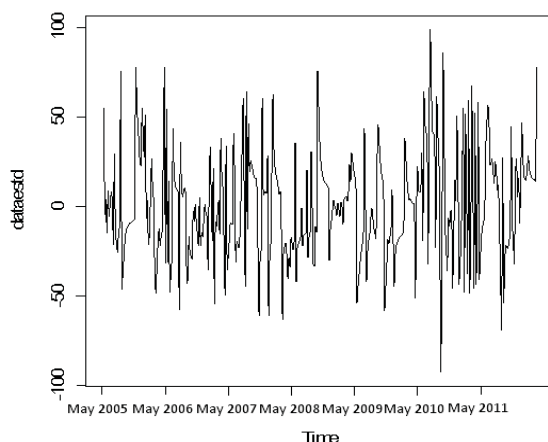


Figure 4. Opening Price Data of Kedaung Indah Can Tbk Stock After Differencing.

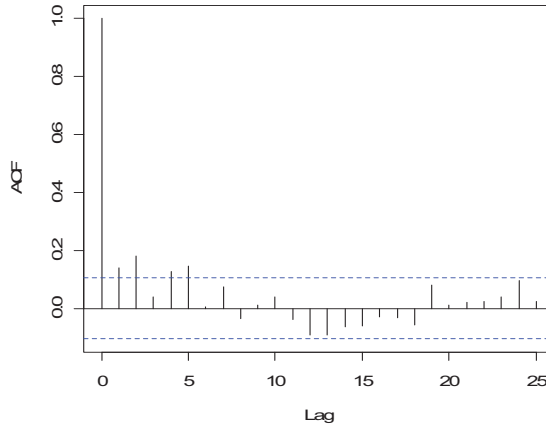


Figure 5. ACF of Opening Price Kedaung Indah Can Tbk Stock After Differencing $d = 0.452$.

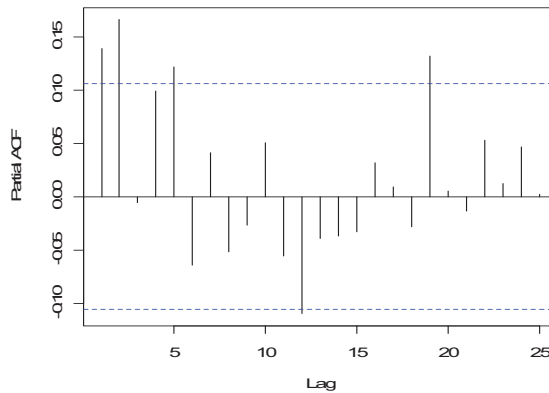


Figure 6. PACF of Opening Price Kedaung Indah Can Tbk Stock After Differencing $d = 0.452$.

Plot the time series after differencing can be seen in Figure 4, in addition ACF and PACF plot after differencing is presented in Figure 5 and Figure 6. Figure 5 shows that the lag q is cut at lag 1, 2, 4, and 5, whereas in Figure 4.2.3 show that the lag p is cut at lag 1, 2, 5, 12, and 19. Therefore, there are few estimates of ARFIMA(p,d,q) model to be tested. After going through the process of sorting between the AIC, AICC, and BIC, ARFIMA model is obtained (5,0.452,4) as the best model with the value of AIC = 3309.67, AICC = 3310.33, and BIC = 3348.07.

3.4. Diagnostic Checking

After obtained a model with significant parameters, it is necessary to do diagnostic tests including checking residuals wheter they are independent and normally distribution or not. To examine the

independent of residual, it is used Ljung-Box test. The results of Ljung-Box test is obtained with $p\text{-value} = 0.9171 \geq \alpha$ for $\alpha = 0.05$, this means that the ARFIMA(5,0.452,4) model has been qualified by the independent of residual white noise. In addition to testing the residuals are independent, also tested whether the residuals are normally distributed using the Kolmogorov Smirnov test. Results obtained from the Kolmogorov Smirnov is a value of $D = 0.054$ and $p\text{-value} = 0.2685 \geq \alpha$. This means that the residuals is normally distributed. Therefore ARFIMA(p,d,q) model which can be used at this stage of the forecasting is ARFIMA(5,0.452,4) model.

3.5. Forecasting

On the opening price data from Kedaung Indah Can Tbk stock is obtained ARFIMA(5,0.452,4) as the best model that can be used in forecasting. The model can be written as follows

$$\phi_5(B)\nabla^{0.452}X_t = \theta_4(B)Z_t$$

$$(1 - 0.7863B - 0.2094B^2 - 0.2534B^3 + 0.7113B^4 - 0.1108B^5)(1 - B)^{0.452}X_t = (1 - 7068B - 0.1572B^2 - 0.4354B^3 + 0.8494B^4)Z_t.$$

Table 1: Forecasting Result of Indah Can Tbk opening stock price.

Date	Actual	Forecast	Se
02/04/2012	215	248.9972	29.56453
09/04/2012	245	248.7835	34.89799
16/04/2012	250	233.1545	39.15815
23/04/2012	255	241.9793	41.40609
30/04/2012	240	240.8529	41.14317

Index: se is square error.

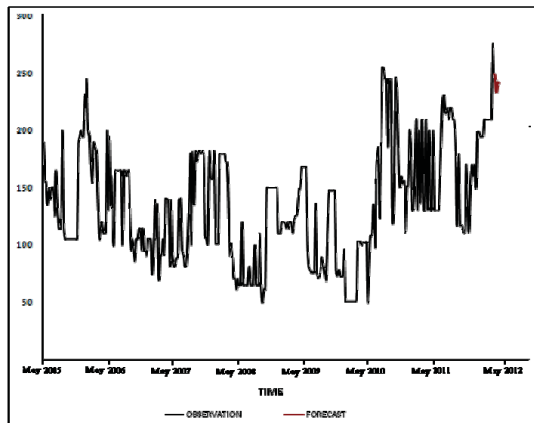


Figure 7. Opening Price Data of Kedaung Indah Can Tbk Stock and Forecasting.

The forecasting results of ARFIMA(5,0.452,4) model for April 2012 are shown in Table 1 and Figure 7. Table 1 is showing that result of forecasting for April 2012 having value which is close enough to its actual data. This is to confirm ARFIMA model has given best suited for long memory process.

4. CONCLUSION

In this paper, it is studied forecasting long memory time series for stock price with model autoregressive fractionally integrated moving average. This model is denoted by ARFIMA(p,d,q), that is

$$\phi_p(B)\nabla^d X_t = \theta_q(B)Z_t,$$

where $\{Z_t\}$ is white noise, $\phi_p(B) = 1 - \phi_1 B - \dots - \phi_p B^p$, $\theta_q(B) = 1 + \theta_1 B + \dots + \theta_q B^q$, and ∇^d is the fractional difference operator with d real number is located at $0 < d < 1/2$. The model ARFIMA(p,d,q) is applied to the opening price data of Kedaung Indah Can Tbk stock from May 2nd 2005 until March 26th 2012, the best suited model is ARFIMA (5,0.452,4). This model is good enough to forecast short time prediction for long memory time series where forecasting result is very close to actual data with small square error.

5. REFERENCES

- Bisaglia. Model Selection for Long Memory Model. Quaderni di Statistica; 2002, Vol. 4.
- Boutahar M and Khalfaoui R. Estimation of the Long Memory Parameter in Non-Stationary Models: A Simulation Study. GREQAM; 2011, version 1-23 May 2011.
- Brockwell PJ and Davis RA. *Time Series: Theory and Methods*. Springer-Verlag. New York. 1991.
- Granger WL and Joyeux R. An Introduction to Long Memory Time Series Models and Fractional Differencing. Journal of Time Series Analysis 1; 1980, 15-29.
- Haslett J and Raftery AE. Space Time Modeling with Long Memory Dependence: Assessing Ireland's Wind Power Resource. Applied Statistics; 1989, Vol. 38, No.1, 1-50.
- Hosking JRM. Fractional Differencing. Biometrika; 1981, Volume 68, 165-176.
- Hurst HE. Long-Term Storage Capacity of Reservoirs. Trans. Am. Soc. Civil Eng.; 1951, 116:770-779.
- Palma W. *Long-Memory Time Series*. John Wiley and Sons, Inc. New Jersey. 2007.
- Wei WWS. *Time Series Analysis*. Addison Wisley Publishing Company. Canada. 1990.