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Grey system based novel forecasting and portfolio mechanism on CSE

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Abstract

Purpose – Because of the high volatility with unstable data patterns in the real world, the ability of forecasting price indices is notoriously embarrassing and represents a major challenge with traditional time series mechanisms; especially, most of the traditional approaches are weak to forecast future predictions in the high volatile and unbalanced frameworks under the global and local financial depressions. The purpose of this paper is to propose a new statistical approach for portfolio selection and stock market forecasting to assist investors as well as stock brokers to predict the future behaviors.

Design/methodology/approach – This study mainly takes an attempt to understand the trends, behavioral patterns and predict the future estimations under the new proposed frame for the Colombo Stock Exchange (CSE), Sri Lanka. The methodology of this study is carried out under the two main phases. In the first phase, constructed a new portfolio mechanism based on k-means clustering. In the second stage, proposed a nonlinear forecasting methodology based on grey mechanism for forecasting stock market indices under the high-volatile fluctuations. The autoregressive integrated moving average (ARIMA) predictions are used as comparison mode.

Findings – Initially, the k-mean clustering was applied to pick out the profitable sectors running under the CSE and results indicated that BFI is more significant than other 20 sectors. Second, the MAE, MAPE and MAD model comparison results clearly suggested that, the newly proposed nonlinear grey Bernoulli model (NGBM) is more appropriate than traditional ARIMA methods to forecast stock price indices under the non-stationary market conditions.

Practical implications – Because of the flexible nonlinear modeling capability, proposed novel concepts are more suitable for applying in various areas in the field of financial, economic, military, geological and agricultural systems for pattern recognition, classification, time series forecasting, etc.

Originality/value – For the large sample of data forecasting under the normality assumptions, the traditional time series methodologies are more suitable than grey methodologies. However, the NGBM is better both in model building and *ex post* testing stagers under the s-distributed data patterns with limited data forecastings.

Keywords Portfolio selection, ARIMA, GM (1,1), GM(2,1), NGBM

Paper type Research paper

1. Introduction

Forecasting and portfolio selection under the high volatility represents one of the most appreciable as well as significant area in fields of science, finance and engineering, both from theoretical and practical perspectives; especially, time series analysis is an essential tool which has been widely applying for identifying

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the meaningful characteristics to make future judgments in economic and finance. Miscellaneous type of time series methodologies under the different categories can be seen in the literature. Some of them are; frequently domain vs the time domain and qualitative vs quantitative.

In the first scenario, all these methodologies under the time domain can be divided into another two sub-categories as parametric and non-parametric. Basically, the parametric approaches have been developed under the basis on the stationary stochastic process that can be described by using the very limited number of parameters. Among the thousand types of qualitative methods, Delphi methods, trend prediction methodologies and expert systems are more significant. Further, quantitative forecasting methods include simple and multiple regressive analysis, exponential smoothing, time series forecasting with new hybrid approaches, grey forecasting methodologies, etc.

Because of the high volatility with unstable data patterns in the real world, the ability of forecasting price indices is notoriously embarrassing and represents a major challenge to traditional time series mechanisms; especially, most of the traditional approaches are weak to forecast future predictions in the high volatile and unbalanced frameworks under the global and local financial depressions. For an example, the well-balanced statistical assumptions with Box-Jenkins methodology, an autoregressive moving average (ARMA) and it is generalization models of autoregressive integrated moving average (ARIMA) are giving high-accurate forecasting results under the stabile platforms.

As a result, miscellaneous types of new methodologies have been developed and proposed under the different assumptions during the past few decades. Some of them include the neural network with hybrid approaches to predict real-world indices (Kohzadi *et al.*, 1996; Kaastra and Boyd, 1996; Darbellay and Slama, 2002; Tseng *et al.*, 2002; Zhang *et al.*, 2012; Valipour *et al.*, 2013; Asadi *et al.*, 2013), genetic algorithms to choose optimal portfolio (Willett, 1995; Maimon and Braha, 1998; Tapan, 1999; Li *et al.*, 2004; Zhang, 2006; Zhang and Babovic, 2011, 2012) the fuzzy logic and forecasting techniques for market tracking and portfolio selections (Lim *et al.*, 2014; Kocadağlıa and Keskin, 2015; Balbás *et al.*, 2016; Chourmouziadis and Chatzoglou, 2016), rough set for data classifications and portfolio selections (Mossin, 1968; Steinbach, 2001; Leung *et al.*, 2012; Castellano and Cerqueti, 2014) and grey prediction mechanisms (Shih *et al.*, 2011; Cui *et al.*, 2013; Chang *et al.*, 2015; Zeng *et al.*, 2016).

As a subset of the literature refers to the forecasting, very few studies have been focussed and attempted to find out the short-term forecasting with limited sample observations (weekly, monthly or quietly). Among them, recently developed grey theory and its estimated new methodologies have become a very effective for solving uncertainty problems with discrete data and incomplete information.

As initially, the Grey system theories (GST) introduced by Deng Julong in 1982 under the three criterions include incidence analysis, clustering analysis and forecasting (Deng, 1989; Kayacan *et al.*, 2010). Within very short period of time, this new proposed methodology has been developed and spread all over the world. Currently, this novel methods successfully applied to generate system modeling with limited data observations in different fields in economy, finance (Hsu *et al.*, 2009; Chen *et al.*, 2010; Rathnayaka *et al.*, 2014, 2015a), seismology (Chen and Huang, 2013; Xia and Wong, 2014), engineering (Hsu, 2010; Xu *et al.*, 2011), energy (Hsu, 2003; Rathnayaka, 2014; Xu, 2015), etc. (Wang *et al.*, 2006; Bin and Qing-sheng, 2010).

Generally, GM(β, δ) and grey Verhulst models are widely used in the literature, where δ represent the βth order partial differential equation. Among them, GM(1, 1) is most applicable for observed data with exponential distributions. Theoretically, it denotes a single variable first-order linear model which can be emphasized only for a limited number of data observations required to construct the forecasting models. Further GM(2, 1) is also used as an alternative prediction dynamic model in different fields.

Generally, the estimated models are not fully perfect under the different theoretical and practical aspects. In the grey modeling scenario, researchers pointed out some significant issues that, the predicted accuracy of grey model is unsatisfied and gives low-accuracy forecasting under the high volatility and unstability; especially economic and financial data under the miscellaneous type of economic booms, economic bubbles (sometimes referred to as a market bubble, a financial bubble, a speculative mania or a balloon). Hence, establishing a new combined prediction model in cooperated with other time a series technique is more essential today.

As a result, by integrating both mathematical and statistical assumptions with computational algorithms, researchers have been developed novel grey mechanisms to solve real-world applications under the five different aspects which include grey prediction, grey relation, grey decision, grey programming and grey control; especially, these new mechanisms such as nonlinear grey Bernoulli model (NGBM) and its generalized model of Nash equilibrium (Chen, 2008; Chen *et al.*, 2010), Grey-fuzzy (Wang, 2002; Wen, 2004), Grey-Taguchi (Yao and Chi, 2004; Chang, 2005), Grey-Markov and its generalized approach of Grey-Fourier (Jegadeesh and Titman, 2001; Hsu, 2003), Grey-depersonalized (Tseng *et al.*, 2001; Liu *et al.*, 2004) provide a wide and powerful technical support for forecasting various fields such as the stock price forecasting, robot fuzzy control, invested pendulum controls, etc.

Moreover, very recently Rathnayaka and Seneviratne (2014) carried out a different type of research study and proposed a new Grey mechanism to estimate the bi-directional relationships between the carbon emissions, energy consumption and economic growth in China. In the same period of time, Zhao *et al.* (2012) conducted another study and developed a high-precision hybrid method to forecast the per capita annual net income of rural house holders in China. Zhou and He (2013) further study to simulate and forecast the fuel production in China.

The prices of the stocks are highly volatile and moving up and down very shortly. As a result, makings decision in equity markets have been regarding as the one of the biggest challenge in the modern economy; especially, analyzing and forecasting unstable data patterns in developing stock markets with limited sample observations under the different economic policies and reforms. The current study will mainly focus and attempted to introduce new portfolio mechanism for assisting investors and stock brokers to predict the future behaviors as well as manage their portfolio mechanisms.

The methodology of this study is running under the two main phases as follows. The first phase developed a new portfolio mechanism by combing the k-means clustering technique with Markowitz portfolio theory to manage their portfolio mechanisms. The second phase, NGBM is applied to forecast short-term predictions with limited sample observations. The results are implemented on Colombo Stock Exchange (CSE), Sri Lanka over the six year period from June 2009 to November 2015.

To achieve these objectives, the remainder of the paper is organized as follows. Section 2 presents the overview of theoretical background of traditional time series approaches such as ARIMA, ARX and grey theory is discussed. The empirical results with comparisons are shown in Section 3. Section 4 gives the discussion and ends up with the conclusion, policy issues and future work.

2. Methodology

2.1 Overview of NGBM

The GST was first presented by Chinese scholar, namely, Deng Julong in 1982. Generally, the grey predicting models contain three operators, namely, accumulated generation, inverse accumulated generation and grey modeling. Initially, the GM(1,1) is a simplest and one of the widely adopted methodology in the literature (Deng, 1989; Xu *et al.*, 2011; Rathnayaka and Seneviratne, 2014). In general, it is a single order, single variable differential equation giving poor predictions under the high volatility.

As a result, by using concepts of traditional GM(1,1) with Bernoulli concepts, the numerous type of NGBMs were introduced and developed for forecasting limited number of row data samples in the literature. The NGBM is constructed as follows (Rathnayaka *et al.*, 2015a, b):

Step 1: the original sequence $X^{(0)}$ where:

$$X^{(0)} = \{x^{(0)}(1),\ x^{(0)}(2), \ldots,\ x^{(0)}(n) | n \geqslant 4\} \tag{1}$$

Assume that $X^{(0)}$ is non-negative row data series, where an original series of row data contains n entries.

Step 2: the corresponding first order accumulated generating operation (AGO) series is given by:

$$AGO(x^{(0)}) \colon X^{(1)} = \{x^{(1)}(1),\ x^{(1)}(2), \ldots,\ x^{(1)}(n)\} \tag{2}$$

where $X^{(1)}$ is given by:

$$x^{(1)}(i) = \sum_{m=1}^{i} x^{(0)}(m), \quad i = 1,\ 2, \ldots,\ n \quad n \geqslant 4 \tag{3}$$

The $AGO\, X^{(0)}$ represents the first order accumulated generating operator, which datum bound comprises both row and generated components crystallized as:

$$x^{(1)}(i) = x^{(0)}(i) + x^{(1)}(i-1)$$

Step 3: the $Z^{(1)}$ denotes the averaging adjoining data in mean consecutive neighbors generating operator for $X^{(1)}$. The $Z^{(1)}$ represent as:

$$MEAN\left(X^{(1)}\right) \colon\ Z^{(1)} = \{z^{(1)}(1),\ z^{(1)}(2), \ldots,\ z^{(1)}(n)\} \tag{4}$$

where $Z^{(1)}(i)$ is given by:

$$Z^{(1)}(i) = MEAN\ X^{(1)} = \frac{1}{2}\left(X^{(1)}(i) + X^{(1)}(i-1)\right); \quad i = 2,\ 3, \ldots,\ n \quad n \geqslant 4 \tag{5}$$

Step 4: the NGBM with its whitenization equation for the non-negative original data sequence is given by $X^{(0)} = \{x^{(0)}(1),\ x^{(0)}(2), \ldots,\ x^{(0)}(n) | n \geqslant 4\}$.

$$x^{(0)}(i)+a\,z^{(1)}(i)=b\left[z^{(1)}(i)\right]^{\gamma} i=2,\ 3,\ldots,\ n \text{ and } \gamma=2,\ 3,\ldots \tag{6}$$

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=b\left(x^{(1)}\right)^{\gamma} \tag{7}$$

where a and b are unknown parameters. The system can be converted for the augmented matrix as follows:

$$\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} = \begin{bmatrix} -z^{(1)}(2) & \left(z^{(1)}(2)\right)^{\gamma} \\ -z^{(1)}(3) & \left(z^{(1)}(3)\right)^{\gamma} \\ \vdots & \vdots \\ -z^{(1)}(n) & \left(z^{(1)}(n)\right)^{\gamma} \end{bmatrix} \begin{pmatrix} a \\ b \end{pmatrix}$$

where:

$$Y_n=BU, \quad \begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix} = \left(B^T B\right)^{-1} B^T Y,$$

where B and Y imply the accumulated matrix and constant vector, respectively.

Step 5: based on the dimensions of γ, the model selection criteria can be defined as follows:

$$\text{Grey model} = \begin{cases} \text{GM}(1,1) & \text{if } \gamma=0 \\ \text{Grey}-\text{Verhulst} & \text{if } \gamma=2 \\ \text{NGBM} & \text{if } \gamma \geqslant 2 \end{cases}$$

If $\gamma=2$; the Grey Verhulst model.

Based on the grey system methodology, the new concept was introduced by Pierre Franois Verhulst for forecasting exponential behavioral data patterns. The new methodology can be defined based on following steps (Bin and Qing-sheng, 2010; Chen *et al.*, 2010; Zhou, 2013).

The time response sequence of grey Verhulst model may be written as:

$$\hat{x}^{(1)}(k+1)=\frac{1}{D+C\,e^{ak}} \tag{8}$$

where:

$$C=\left[\frac{1}{x^{(1)}(1)}-D\right] \text{ and } D=\frac{b}{a}$$

If $\gamma>2$; the NGBM model.

According to the first-order differential conditions, the particular solution for whitening equation can be expressed as:

$$\hat{x}^{(1)}(i+1)=\left[\left(x^{(0)}(1)^{1-n}-D\right)e^{-a(1-n)k}+D\right]^{1/(1-n)}\ n\neq 1 \text{ and } k=1,\ 2,\ 3,\ldots \tag{9}$$

Step 6: to obtained the fitted values and predicted values, the inverse accumulated generating operation may be applied:

$$\hat{x}^{(0)}(i+1) = \hat{x}^{(1)}(i+1) - \hat{x}^{(1)}(i); \quad i = 1, 2, 3, \ldots, n$$

$$\hat{x}^{(1)}(1) = x^{(0)}(1)$$

where $\hat{x}^{(0)}(n+1)$, $\hat{x}^{(0)}(n+2)$, $\hat{x}^{(0)}(n+3)$, … are forecasted values of the grey Verhulst model.

2.2 New hybrid statistical approach for portfolio selection

The main purpose of this study is to develop a new portfolio mechanism for assisting investors as well as stock brokers to predict the future behaviors and manage their portfolio mechanisms. Further, NGBM-based grey mechanism is used for forecasting stock market indices under the high-volatile fluctuations. The ARIMA predictions are used as comparisons.

Step 1: variable selection. The linkage between the type of variable, data source and data collection strategies can help to determine the appropriate model. The frequency of the data totally depends on with research objectives and research targets. In generally, economic and finance data will depend on the variable to measure and the resources available. The proposed method specifies the following attributes; daily closing stock prices, trade values and turnover values, sector market capitalization and stock market price indices.

Step 2: data preprocessing. As a next step, before analyzing the data, transforming the inputs to minimize the noise, discover the trends and identify the relevant patterns. Two types of significant data transformations can be seen in the literature. They are; first differencing and convert data to the natural log of the variables. Furthermore, two unit root methods, namely, Augmented Dickey-Fuller (ADF) test statistic and Phillips-Perron (PP) test statistic can be used to check the data set is stationary or not (Jayathileke and Ratnayake, 2013; Rathnayaka *et al.*, 2015a, b).

Step 3: k-means clustering methodology. The k-means clustering is a method that used to classify semi-structured or unstructured data sets; especially, this is one of the most common and effective methods for classifying the voluminous data sets. The centroid of the cluster to which the item was assigned is recalculated (Rathnayaka and Wang, 2012). This distance is usually the Euclidean Distance (Arumawadu *et al.*, 2015):

$$d_{euc} = \sum_{i=0}^{n} \sqrt{(x_i - c_i)^2} \tag{10}$$

where d_{euc}, x_i represent the Euclidean Distance and *i*th point in cluster, respectively.

Step 4: training, testing and validations and data forecasting. In this proposed system, short-term grey operational forecasting models such as GM(1,1), GM(2,1), grey Verhulst and NGBMs used for forecasting price indices as a comparison purpose. Furthermore, as a comparison mode the selected ARIMA models and ARX methodologies used to assess the out-of-sample forecasting performance for the horizon of one week ahead (testing sample).

The basic processing steps in the new proposed methodology can be summarized as follows in Figure 1.

Having completed all the steps which were describe above, as final step investors can allocate their capitals for better selected stocks.

3. Empirical results on CSE

3.1 Data and preprocessing

Highly volatile fluctuations with instability patterns are the common phenomenon in the CSE, Sri Lanka. Because of innumerable micro- and macro-economic conditions with international and local political changes are directly involved (Rathnayaka *et al.*, 2014, 2015a, b). Theoretically, the higher volatility always poses higher risk and returns for the investments.

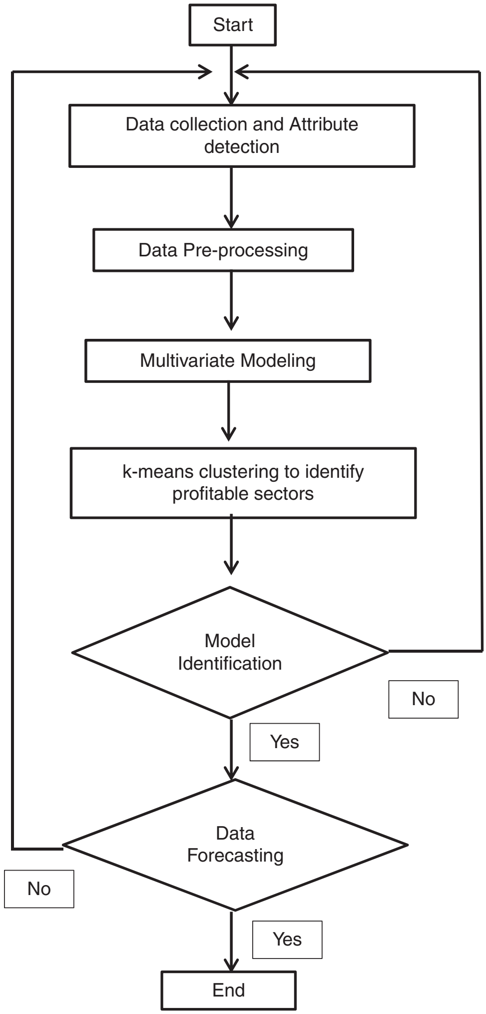

Figure 1.
Flow chart of forecasting and stock selection

The proposed forecasting and stock selection model was carried out on the basis of secondary data, which were obtained from CSE daily and monthly financial statements, other relevant sources, etc. Two main price indices, namely, All Share Price Index (ASPI) and the Standard & Poor's Sri Lanka 20 (or S&P SL20) and sector vise indices were mainly used.

The political stability of the country directly influences to the market fluctuations. For an example, since end of the Civil War on 18 May 2009, the CSE indices have been increased rapidly with a huge market capitalization. The first time in the CSE history, ASPI indices has achieved the historical milestone and surpassed over the 3,000 limits.

The year vice data patterns in Figure 2 clearly show that, the ASPI and SL20 are fluctuating high volatility.

3.2 Stationary/non-stationary model checking

Theoretically, a unit root is a feature of the process that adjusted through time that can cause problems in statistical inference involving time series models. As a next step, unit root test used to test whether the selected data series existence of stationary of unit root or not. Two significant methods, namely, ADF and PP test methods were used.

Table I results suggested that data are significantly stationary in their first differences under the 0.05 level of significance.

3.3 New portfolio optimization methodology for stock allocations

In the next stage, k-clustering algorithm was applied to categorize the profitable sectors which are trading under the CSE. As an initial step, the Principal Analysis (PCA) was performed to identify the exact number of clusters and in order to find any groups of stocks that exhibit similar patterns in returns based.

The eigenvalues of the covariance matrix and the proportion of variations explained by each principal component corresponding to each eigenvalues are given in Table II.

Table II results indicate that the first two components collectively explain more than 80.8 percent of the total variation in the original data set. The first three components collectively explain 88.6 percent of the total variation. Further, the drop in the proportion of variation explained by each principal component is not significant when component moving from third to fourth. Hence, up to three components will be considered for further analysis.

In the next stage k-clustering algorithm was applied to clarify the profitable sectors among the 20 sectors which are trading under the CSE. The average linkage method with three number of clusters (identified from PCA) was used.

Dendrogram suggests variables which might be combined, perhaps by averaging or totaling. In this scenario, dendrogram in Figure 3 and the score plot in Figure 4 suggested that, the banks, finance and insurance (BFI), diversified holdings (DIV), construction and engineering (CE) and telecommunication (TEL) sectors can be categorized in a one group and beverage, food and tobacco (BFT), land and property (LP), manufacturing (MAN), healthcare (HEA) and power and energy (PE) can be categorized in other group; especially, in the both sides the BFI and BFT sectors have been trading their peak during the past five years.

As a next step, two selected profitable sectors, namely, BFI and DIV from left hand clustering and LP and MAN from right hand clustering were selected for our further analysis.

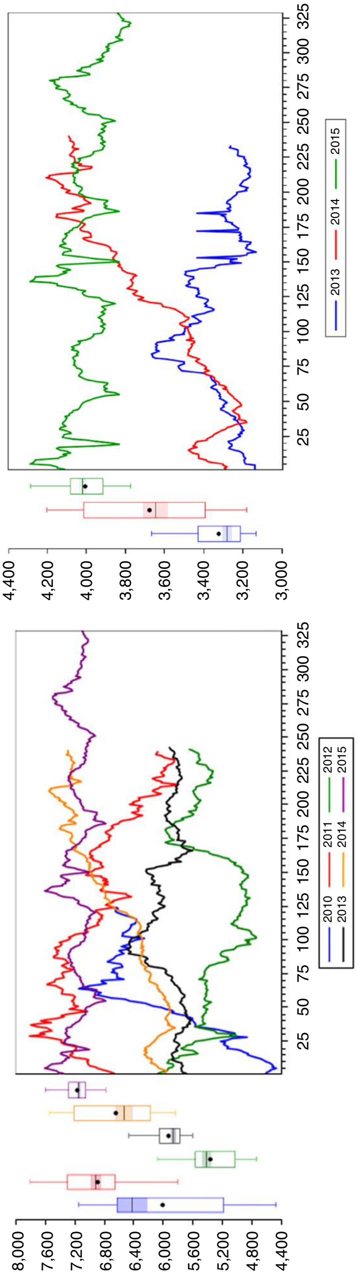

Figure 2.
ASPI and SL20 fluctuations yearly

3.4 Model fitting and data forecasting

Based on their last two quarter performances from June to November 2015, daily trading data were extracted and tabulated. Data patterns in Figure 5 suggested that BFI and DIV were fluctuating with high volatility under the unstable manner.

Theoretically, the ARMA and its generalized model of ARIMA are more suitable and applicable for predicting future results. As a next step, appropriate forecasting models were identified based on minimum values of Akaike information (AIC), Schwarz (SC) and Hannan-Quinn (HQC) criterions (Table III).

The minimum value of AIC (12.77188), SC (12.78674) and HQC (12.77787) in BFI and AIC (8.666968), SC (8.726577) and HQC (8.691011) in DIV suggested that ARMA (1, 1, 0) and ARIMA (2, 1, 2) are more suitable for forecasting future behaviors, respectively. However, the model accuracy testing results in Table IV suggested that selected linear time series models are not fully suitable and appropriate under the non-stationary behavioral patterns.

	Significant result Level data			Significant result Level data	
Price index	ADF	PP	Price index	ADF	PP
ASPI	0.5945	0.5225	ASPI	0.0000	0.0000
SL20	0.3923	0.4212	SL20	0.0000	0.0000
STM	0.4325	0.4432	STM	0.0000	0.0000

Note: All the tests assume asymptotic normality

Table I. ADF and PP test results

Component number	1	2	3	4	5	6 or more
Eigenvalue	10.389	7.381	1.720	0.806	0.397	
Proportion	0.472	0.336	0.078	0.037	0.018	
Cumulative %	0.472	0.808	0.886	0.923	0.941	≈1

Table II. Eigenvalues of the covariance matrix

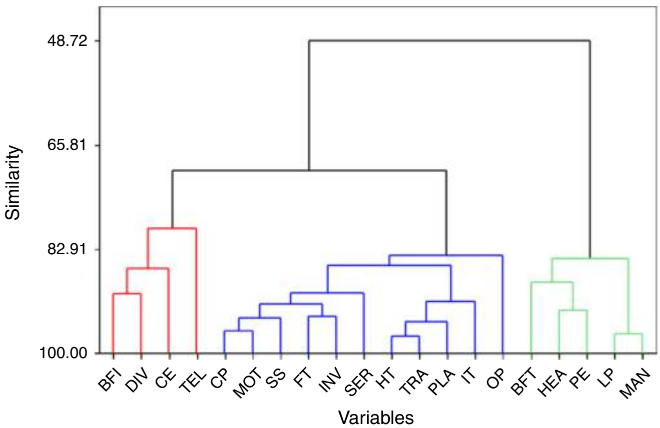

Figure 3. Dendrogram plot for CSE sectors

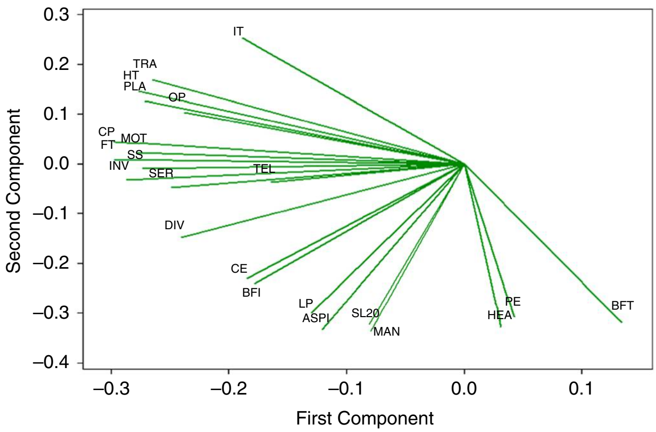

Figure 4.
Score plot for CSE sectors

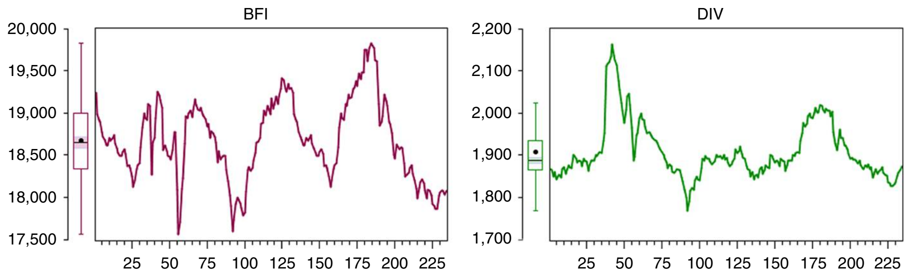

Figure 5.
Run sequence plot for BFI and DIV

Table III.
The model selection criterion for ARIMA: ASPI price index

BFI				DIV			
p/q	0	1	2	p/q	0	1	2
0		12.77506	12.78204	0		8.648523	8.651785
		12.78987	12.81166			8.663334	8.681408
		12.78103	12.79398			8.654495	8.66373
1	12.77188	12.77564	12.77845	1	8.649488	8.657016	8.658797
	12.78674	12.80535	12.82302		8.664344	8.686729	8.703367
	12.77787	12.78762	12.79643		8.655479	8.668999	8.676772
2	12.77916	12.85188	12.89732	2	8.658128	8.658797	8.666968
	12.80897	12.81631	12.84381		8.687933	8.703367	8.726577
	12.79118	1.997387	2.004684		8.670149	8.676772	8.691011

Notes: Yellow color boxes indicate the significant results under 0.05 levels of significance and Red color indicates the minimum value of AIC, SC and HQC errors

So, as a next step, grey operational models, namely, GM(1, 1), GM(2, 1), grey Verhulst and new proposed NGBMs used to forecasting price indices for comparison purpose.

The model accuracy testing results in Tables IV and V show that the NGBM model gives the minimum MAPE, MAD and RMSE than others. So, NGBM with over daily data returns implies the best simulation result than other models.

The error bar plot results in Figure 6 also suggested that NGBM model created low-error accuracies than other models. All these results concluded that, NGBM is better both in model building and *ex post* testing stagers under the *s*-distributed data patterns.

4. Concluding remarks

Both empirical results suggested that linear and nonlinear separate methods are not sufficient and enough to forecast modern financial indices under the high volatility. Furthermore, most of these approaches are more suitable and appropriated only just for empirical data studies under the normality, linearity and stationary assumptions. For example, some forecasting models are great at short-term predictions, but cannot capture the seasonality or variability with very limited number of sample observations; especially to predict stock price trends for highly nonlinear and non-stationary random time sequences with noise data (Rathnayaka *et al.*, 2015a, b).

As a result of these complications regards to the traditional time series approaches, NGBM is more suitable and appropriate to handle incomplete, noise and uncertain data in multidisciplinary systems. Because of the flexible nonlinear modeling capability, proposed novel concepts are more suitable for applying in various systems such as financial, economic, military, geological and agricultural systems for signal processing, pattern recognition, classification, time series forecasting, etc.; especially, grey mechanism's-based methodologies are more suitable for forecasting stock market predictions than others under the nonlinear high volatility.

			BFI		
Model accuracy	ARIMA	GM(1, 1)	GM(2, 1)	Verhulst	NGBM
June 5, 2015 to August 30, 2015 (Q1)					
MAPE	0.078068	0.464798	0.269703	0.15265	0.038072
MAD	5.17459	32.328	18.768	10.628	2.65
RMSE	5.655985	39.03961	21.39443	11.6735	3.169224
2 September, 2015 to November 30, 2015 (Q2)					
MAPE	0.022153	0.25835	0.15444	0.07315	0.016025
MAD	1.500712	18.27062	10.918	5.174	1.134
RMSE	1.752443	19.41791	12.83028	5.48958	1.185555

Table IV. The BFI model accuracy for third quarter 2015

			DIV		
Model accuracy	ARIMA	GM(1, 1)	GM(2, 1)	Verhulst	NGBM
June 5, 2015 to August 8, 2015 (Q1)					
MAPE	0.460182	0.1715	0.180474	0.15017	0.060261
MAD	16.17987	6.99722	7.38	6.136	2.462
RMSE	19.8725	9.647412	8.781783	8.33022	4.012608
September 2, 2015 to November 30, 2015 (Q2)					
MAPE	0.240124	1.578952	0.75388	0.42788	0.128276
MAD	11.10662	60.44222	28.862	16.38	4.906
RMSE	12.00135	62.90244	31.79141	17.7425	5.737841

Table V. The DIV model accuracy for fourth quarter 2015

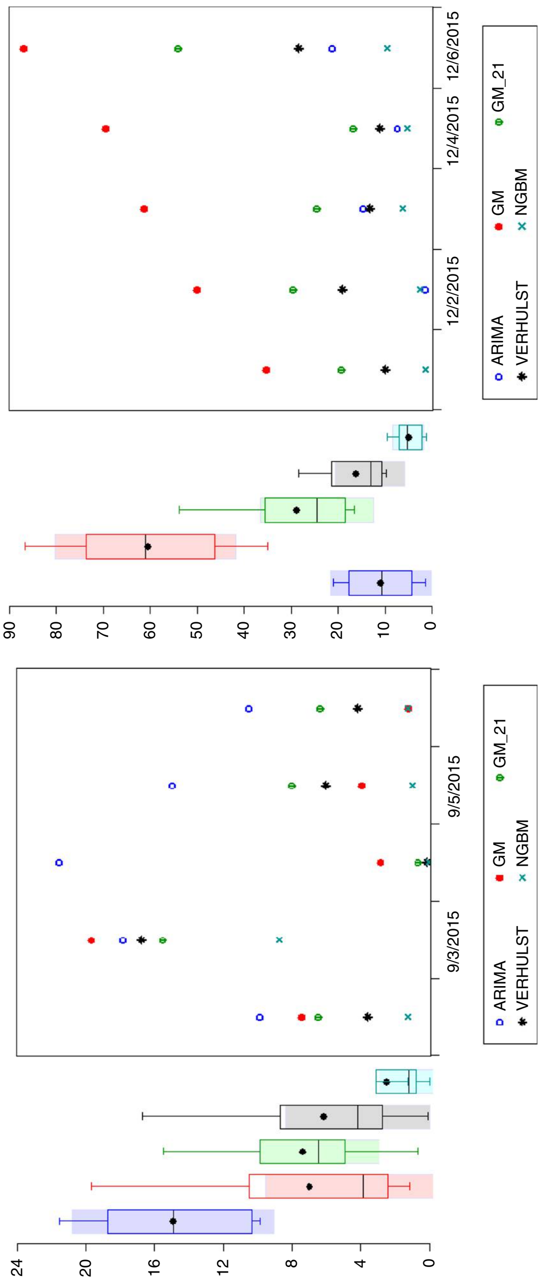

Figure 6.
Error bar plot for DIV quartile (Q1 and Q2) data forecasting

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