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Grey system based novel approach for stock market forecasting

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Abstract

Purpose – Making decisions in finance have been regarded as one of the biggest challenges in the modern economy today; especially, analysing and forecasting unstable data patterns with limited sample observations under the numerous economic policies and reforms. The purpose of this paper is to propose suitable forecasting approach based on grey methods in short-term predictions.

Design/methodology/approach – High volatile fluctuations with instability patterns are the common phenomenon in the Colombo Stock Exchange (CSE), Sri Lanka. As a subset of the literature, very few studies have been focused to find the short-term forecastings in CSE. So, the current study mainly attempted to understand the trends and suitable forecasting model in order to predict the future behaviours in CSE during the period from October 2014 to March 2015. As a result of non-stationary behavioural patterns over the period of time, the grey operational models namely GM(1, 1), GM(2, 1), grey Verhulst and non-linear grey Bernoulli model were used as a comparison purpose.

Findings – The results disclosed that, grey prediction models generate smaller forecasting errors than traditional time series approach for limited data forecastings.

Practical implications – Finally, the authors strongly believed that, it could be better to use the improved grey hybrid methodology algorithms in real world model approaches.

Originality/value – However, for the large sample of data forecasting under the normality assumptions, the traditional time series methodologies are more suitable than grey methodologies; especially GM(1, 1) give some dramatically unsuccessful results than auto regressive intergrated moving average in model pre-post stage.

Keywords GM(1, 1) model, CSE, GM(2, 1) model, Grey Verhulst, Non-linear grey Bernoulli model, Decisions in finance

Paper type Research paper

1. Introduction

The time series forecasting is a significant process, which can be widely applied for generating future predictions based on time-dependent series of observed data points. As a result of combination between mathematical, statistical and economical concepts, numerous types of forecasting methodologies have been introduced in the last three decades. Initially, these methodologies have been categorized into three categories as fundamental, technical (chart techniques) and technological methods (Taylor and Allen, 1992). Furthermore, the fundamental technologies have been classified again into another two categories as qualitative and quantitative (Granger, 1989; Ho *et al.*, 2002). The qualitative forecasting techniques are more appropriated when the past data are

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not available or limited. However, quantitative forecasting methods totally depend only on the historical data patterns (see Nobuhiko Terui, 2002; Jain and Kumar, 2007; Fang *et al.*, 2008; Song *et al.*, 2013).

In the last two decades, thousands of forecasting models have been developed for analysing time series data under the miscellaneous type of assumptions; especially, moving average , auto regressive (AR), auto regressive moving average (ARMA), auto regressive integrated moving average (ARIMA) and weighted moving average are playing significant role in the literature (Mills, 1990; Zhang, 2003a, b; Ho *et al.*, 2002; Asteriou and Hall, 2011). However, some of these traditional approaches are not suitable for forecasting time series data under the modern economical as well as financial conditions; especially with high volatile fluctuations with unstable data patterns. As a result, hybrid forecasting models have been created successfully for forecasting real world problems. In the past two decades, significant number of studies have done by Granger (1989), Pack (1990), Poli and Jones (1994), Denton (1995), Zhang *et al.* (1998), Balkin and Ord (2000), Nobuhiko Terui (2002), Ho *et al.* (2002), Zhang (2003a, b), Pai and Lin (2005), Taskaya and Casey (2005), Chakradhara and Narasimhan (2007), Jain and Kumar (2007), Khashei and Bijari (2011) and Rathnayaka *et al.*, 2014. Unfortunately, some of these approaches are more suitable and appropriated just only for empirical data samples under the normality assumptions. For an example, some hybrid 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 non-linear and non-stationary random time sequences with noise data (Priestley, 1988).

As a result of these complications with traditional time series approaches, grey modelling concept was proposed by Chinese scholar Deng Ju-long in early 1980s to solve incomplete, noise and uncertain data in multidisciplinary systems. Within a very short period, this novel concept was popular and has been successfully applied to various systems such as financial, economic, energy consumption, military, geological and agricultural systems (Deng, 1989; Xuerui *et al.*, 2007).

Generally, two grey models are frequently used in the literature. They are; GM(β,δ) and grey Verhulst model, where δ represent the βth order partial differential equation. Among them, GM(1, 1) is most suitable 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 for constructing the forecasting models. Indeed, the accumulated generating operation (AGO) is widely used to reduce the randomness of the distribution. It means that, the new series force to reduce the noise than original series after converting it into a monotonically increased series. As a result, AGO is more suitable for identifying the systematic regularity with respect to the time (Deng, 1989).

In the past 30 years, miscellaneous type of research studies have been carried out to find some accuracy models based on GM(β,δ) methodologies. According to the literature, Trivedi and Singh (1992), Wang and Hsu (1995), Zhou *et al.* (2006) and Rathnayaka and Seneviratna, 2014 did remarkable studies to improve the GM(1, 1) forecasting accuracy rather than traditional approachers; especially, non-linear grey prediction models such as GM(2, 1), grey Verhulst and grey Bernoulli model have developed for the oscillatory distributions, saturated distributions and highly fluctuate distributions, respectively. For an example, Zhang (2003a, b), Wang *et al.* (2006) and Wang *et al.* (2006) successfully applied the grey Verhulst model for forecasting long-term road and load traffic accidents in China. Furthermore, the Verhulst model can be widely applied to predict the data in the sequence of non-monotone wave type characteristic distributions such as life cycle of the product, forecasting the population growth rates, etc.

The genetic algorithm (GA) based on artificial intelligence is a heuristic (meta-heuristic) search engine, which has been widely applied to find optimum solutions in NP hard problems under the non-polynomial conditions (Chang, 2005). In the recent years, using optimum theory of GAs-based grey hybrid Bernoulli algorithms have been widely applied in different fileds such as computational science, economics and finance (Hsu, 2010), manufacturing (Fang *et al.*, 2008; Hsu, 2010, 2003; Hsu and Chen, 2003) weather forecasting (Nasseri *et al.*, 2008; Jin *et al.*, 2008), pharmacometrics, etc.; especially, researchers have done remarkable studies in finance to forecast price indices in stock markets around the world (Ji and Zhang, 2011; Kayacan *et al.*, 2010; Hsu *et al.*, 2009; Chen *et al.*, 2010).

Rates of the equity markets are highly volatile. Within a very short period of time, the prices of the stocks move up and down with high fluctuations. So, very limited number of forecasting models can be seen in the literature to forecast the stock market indices perfectly with limited number of sample observations. So, the main objective of this study is to examine the most suitable short-term forecasting model for forecasting stock market price indices in Colombo Stock Exchange (CSE), Sri Lanka. The empirical results compare with traditional time series approaches such as ARMA, ARIMA and least squares-based grey models such as GM(1, 1), GM(2, 1), grey Verhulst and new GA-based non-linear grey Bernoulli model (NGBM). Furthermore, accuracy measures such as mean absolute percentage error (MAPE), Mean absolute deviation (MAD) and root mean squared error (RMSE) use to elect the most significant forecasting model among the others.

The rest of the paper is organized as follows. In Section 2, overview of theoretical background of traditional time series approaches such as ARMA and ARIMA 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

The high volatile fluctuations with instability patterns are common phenomenon in the stock markets around the world today; especially, innumerable macro ecconomic and financial factors are directly affected for generating high volatile fluctuations. Indeed, the preformances of stock market are positively influence to the economic development of the country.

The current study mainly deals with mechanisms of explaining the predictive ability and profitability of technical trading strategies in CSE, Sri Lanka. The methodology can be described as follows. In the first phase, stock market validations are identified based on traditional AR methods such as ARMA and ARIMA. In the next, grey operations such as GM(1, 1), GM(2, 1), grey Verhulst with new proposed GA-based NGBM are applied to predict future predictions. In the last, test accuracy techniques are applied to find the suitable model to evaluate short time predictions.

2.1 Overview of grey models accumulation and test of row series: GM(1, 1) model

The grey system theory (GST) was pioneered by Deng Julong in 1982. According to the explanation, first-order one variable grey model GM(1, 1) plays a significant role in data analysing with relatively less data with single time-varying coefficients (Deng, 1989; Xu *et al.*, 2011; Rathnayaka and Seneviratna, 2014). The GM(1, 1) modelling algorithm goes through the following steps:

Step 1:

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

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

Step 2:

The first order accumulated generating operation (AGO) of $X^{(0)}$ series is given by:

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

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

$$x^{(1)}(k) = \sum_{m=1}^{k} x^{(0)}(m), k = 1, 2, \ldots, nn \geqslant 4$$

The $AGOX^{(0)}$ represents the first order accumulated generating operator, which bound comprises both raw and generated components crystallized as:

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

Furthermore, $X^{(0)}$ is the first-order inverse accumulating generation sequence of $X^{(1)}$. where $X^{(0)}(k) = X^{(1)}(k) - X^{(1)}(k)$, $k = 2,3, \ldots, n$.As an initial condition, $X^{(0)}(1) = X^{(0)}(1)$.

Step 3:

The $MEAN(X^{(1)})$ denotes the averaging adjoining data in mean consecutive neighbours generating operator for $X^{(1)}$:

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

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

$$Z^{(1)}(k) = MEANX^{(1)} = \frac{1}{2}\left(X^{(1)}(k) + X^{(1)}(k-1)\right); k = 2, 3, \ldots, nn \geqslant 4$$

Step 4:

Theoretically, $AGO(x^{(0)})$ represents a monotonically increase series, which represents the behaviours of first-order differential equation. Therefore, the solution curve of the first-order differential equation represents the approximation of $AGO(x^{(0)})$ series as:

$$\frac{d\hat{x}^{(1)}}{dt} + a\hat{x}^{(1)} = b$$

where both "a" and "b" are the interim parameters (developmental coefficient) of prediction values of the grey model, respectively. The $x^{(0)}(1) = \hat{x}^{(0)}(1)$ is the initial condition of the model.

According to the definition, $d\hat{x}^{(1)}/dt$ can be defined as follows:

$$\frac{d\hat{x}^{(1)}}{dt} = \lim_{\Delta t \to 0} \frac{\hat{x}^{(1)}(t+\Delta t) - \hat{x}^{(1)}(t)}{\Delta t} \tag{1}$$

If the sampling time interval Δt is unit, then we can assume that, $\Delta t \rightarrow 1$. So equation can be reduced as:

$$\frac{d\hat{x}^{(1)}}{dt} \cong x^{(1)}(k+1) - x^{(1)}(k); k = 1, 2, 3, \ldots, n \tag{2}$$

Based on Equations (1) and (2), the whitenization equation can be defined as follows:

$$x^{(0)}(k) + az^{(1)}(k) = b \quad k = 2, 3, \ldots, n \tag{3}$$

The undetermined parameters a and b are called developmental coefficient and grey input, respectively. The $z^{(1)}(k)$ is said to be mean series of $x^{(1)}(k)$.

Step 5:

To estimate the developing coefficient of grey inputs a and b, the least square estimators with augmented matrix can be obtained as follows:

$$\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \begin{pmatrix} a \\ b \end{pmatrix} \tag{4}$$

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

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

Step 6:

According to the first-order differential equation method, the particular solution of the AGO Grey prediction can be approximate as follows:

$$\hat{x}^{(1)}(k+1) = \left[x^{(1)}(1) - \frac{b}{a}\right] e^{a(k-1)} + \frac{b}{a}; k = 1, 2, \ldots, n$$

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

Step 7:

Substitute AGO (inverse accumulated generating operation (IAGO)) operator from Step 2, the simulation function of $\hat{x}^{(0)}(k+1)$ can be obtained as follows:

$$\hat{x}^{(0)}(k+1) = (1 - e^{-a}) \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak}; k = 1, 2, \ldots, n$$

where $\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \ldots, \hat{x}^{(0)}(n)$ and $\hat{x}^{(0)}(n+1), \hat{x}^{(0)}(n+2), \ldots$ are GM(1, 1) fitted values and forecast values, respectively.

2.2 GM(2, 1) *Model*

In the past decades, numerous type of methodologies have been developed based on the GSTs with GM(1, 1) methodologies; especially GM(2, 1) model has been developed for forecasting non-monotonic sequences with very limited sample observations. The theoretical background of GM(2, 1) has gone as follows (see Lin and Xiao, 2008; 刘丽桑 *et al.*, 2011; Sheu *et al.*, 2014).

Assuming that the original raw data sequence is located as follows:

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

Steps 1 and 2 are going similar way as GM(1, 1).

Step 3:

The series $IAGOX^{(0)}$ is a first-order IAGO, which subtracting the adjoined data in succession:

$$IAGO\left(X^{(0)}\right) = X^{(-1)} = \left(x^{(-1)}(1), x^{(-1)}(2), \ldots, x^{(-1)}(n)\right)$$

For $x^{(-1)}(k) \in IAGO(X^{(0)})$, satisfies that, $x^{(-1)}(k) = x^{(0)}(k) - x^{(0)}(k-1)$ and $x^{(-1)}(1) = x^{(0)}(1)$.

Step 4:

Based on Steps 1-4, the differential equation of grey model GM(2, 1) and its whitenization equations can be expressed as follows:

$$x^{(-1)}(k) + ax^{(0)}(k) + cz^{(1)}(k) = b \quad k = 2, 3, \ldots, n$$

$$\frac{d^2\hat{x}^{(1)}}{dt^2} + a\frac{d\hat{x}^{(1)}}{dt} + cx^{(1)}(k) \cong b; k = 1, 2, 3, \ldots, n$$

where a, c and b are the interim parameters. The augmented matrix is given by:

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

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

where B implies the accumulated matrix and Y denotes the constant vector.

Step 5:

The characteristic function for quadratic Equation (4) is (Washington, 2000; Rich and Schmidt, 2004; Aitken, 2013):

$$\lambda_{1,2} = \frac{-a \pm \Delta}{2}; \ \Delta = \sqrt{a^2 - 4c}$$

Based on the discriminant of characteristics, the simulation functions of $X^{(1)}(k+1)$ can be defined as follows:

$$X^{(1)}(k+1) = \begin{cases} C_1 e^{\lambda_1 k} + C_2 e^{\lambda_2 k} + \frac{b}{c} & if \Delta > 0 \\ e^{\lambda k}(C_1 + C_2 k) + \frac{b}{c} & if \Delta = 0 \\ C_1 \cos\left(\frac{\Delta}{2}k + C_2\right) e^{-\frac{ak}{2}} + \frac{b}{c} & if \Delta < 0 \end{cases}$$

where C_1 and C_2 are undetermined coefficients.

Step 6:

To simulate the predicted values of the $(2,1)$, $\left\{\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \ldots, \hat{x}^{(0)}(n)\right\}$ can be obtained after applying the IAGO predicted equation as follows:

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

where $\hat{x}^{(0)}(n+1), \hat{x}^{(0)}(n+2), \hat{x}^{(0)}(n+3), \ldots$ are forecast values of the GM(2, 1).

2.3 NGBM

By using consepts of traditional GM(1, 1) with Bernoulli methodology, the numerous type of NGBMs were introduced and developed for forecasting limited number of raw data samples in the literature. The NGBM methodology is constructed as follows (Hsu, 2010; Xu *et al.*, 2015).

The Steps 1 and 2 are going same as GM(1, 1).

Step 3:

The NGBM with its whitenization equation for the non-negative original data sequence by $X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)|n \geqslant 4$ can be defined as follows:

$$x^{(0)}(k) + az^{(1)}(k) = b\left[z^{(1)}(k)\right]^{\gamma} \quad k = 2, 3, \ldots, n \text{ and } \gamma = 2, 3, \ldots$$

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

where a and b are unknown parameters. The system can be converted into 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 $Y_n = BU$, $\begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix} = \left(B^T B\right)^{-1} B^T Y$, where B and Y imply the accumulated matrix and constant vector, respectively.

Step 4:

Based on the dimentions of γ, the model selection critea can be difined as follows:

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

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 behavioural data patterns. The new methodology can be defined based on following steps (Guo *et al.*, 2005; Wu and Chen, 2005; Bin and Sheng, 2010; Chen *et al.*, 2010; Yi-Zhang, 2012; Zhou, 2013).

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

$$\hat{x}^{(1)}(k+1) = \frac{1}{D+Ce^{ak}}$$

where $C = \left[\frac{1}{x^{(1)}(1)} - D\right]$ and $D = \frac{b}{a}$, If $\gamma > 2$; the NGBM model.

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

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

Step 5

To be obtained the fitted values and predicted values, the IAGO can be applied:

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

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

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

2.4 Model accuracy testing

Time series forecasting can be comprehensively considered as a method or a technique for predicting future aspects of many operations. To pick out the suitable model for forecasting, three model accuracy standards are employed. They are MAD, MAPE and RMSE methods were used.

The accuracy models are define as follows:

$$MAPE = \frac{1}{n}\sum_{k=1}^{n} \frac{\left|x^{(0)}(k) - \hat{x}^{(0)}(k)\right|}{x^{(0)}(k)}$$

$$MAD = \frac{1}{n}\sum_{k=1}^{n} \left|x^{(0)}(k) - \hat{x}^{(0)}(k)\right|$$

$$RMSE = \sqrt{\frac{\sum_{k=1}^{n}\left(x^{(0)}(k) - \hat{x}^{(0)}(k)\right)^2}{n}}$$

where $x^{(0)}(k)$ and $x^{(0)}(k)$ represent observed and forecast values, respectively. Table I represents the scale of judgement of forecast accuracy regarding the error (MAPE) and clearly indicates that, the minimum values of MAPE make more accuracy for forecasting future predictions (Rathnayaka and Seneviratna, 2014):

MAPE (%)	Judgement of forecast accuracy
< 10	High accurate
11-20	Good forecast
21-50	Reasonable forecast
> 51	Inaccurate forecast

Table I. Scale of judgement of forecast accuracy

3. Empirical results

The current study was carried out on the basis of secondary data, which were obtained from CSE, annual reports from Central Bank of Sri Lanka, CSE account holders, background readings and other relevant sources, etc.

The CSE is the main stock exchange in Sri Lanka with a fully automated trading platform with a well-organized manner than other exchangers in South Asia. As a developing stock exchange, high volatile fluctuations with instability patterns are common phenomenon in the CSE; especially after finishing the civil war in 2009. The data patterns in Figure 1 clearly show that, the stock indices are highly non-linear and non-stationary in the past three years between January 2012 and March 2015.

This study mainly attempted to understand the trend and cyclic patterns in the CSE in order to predict the future behaviours in two major stock indices including All Share Price Index (ASPI) and S&P Sri Lanka 20 Price Index (S&P SL20). Based on their last two quarter performances from October, 2014 to March, 2015, daily trading data were extracted and tabulated for calculations. In this study, the traditional forecasting approaches namely ARIMA with new grey operational models such as GM(1, 1), GM (2, 1), grey Verhulst and NGBMs were used as a comparison purpose.

3.1 Simulation results

As an initial step, stationary and non-stationary conditions were measured based on two different unit root statistics, namely, augmented Dickey-Fuller and Phillips-Perron test statistics. Table II results clearly suggested that, ASPI data are non-stationary in

Table II. Stationary and non-stationary model checking

	Test critical values Level data			Test critical values 1st difference data	
Index	ADF	PP	Index	ADF	PP
ASPI	0.2409	0.5523	ASPI	0.0002	0.0002
SL20	0.0198	0.0003	SL20	0.0000	0.0000

Notes: MacKinnon (1996) one-sided p-values; null hypothesis: D(ASPI) and D(SL20) have unit root

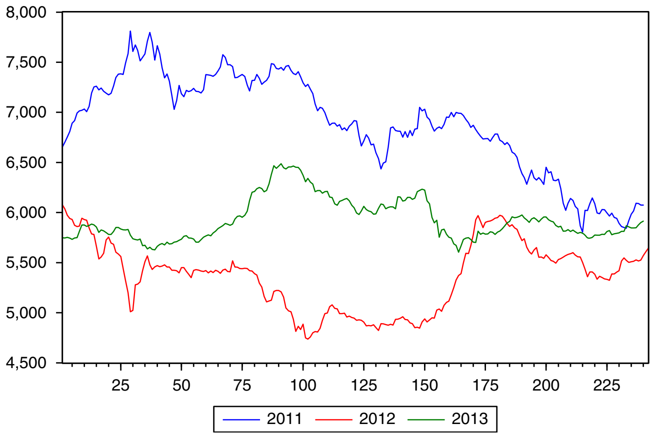

Figure 1. ASPI fluctuations

their levels, but stationary in their first difference under the 0.05 level of significance. However, as a just launched index, S&P Sri Lanka 20 (SL20) has been still fluctuating under the stability manner.

As a next step, the appropriate ARMA and ARIMA forecasting models were identified based on the minimum values of Akaike information (AIC), Schwarz (SC) and Hannan-Quinn criterion (HQC).

The results in Table III clearly indicated that, *ARIMA*(0,1,1) ((AIC (10.7989), SBIC (10.8357), and HQIC (10.8131)) *ARMA*(2, 1) (AIC (10.1917), SBIC (10.3042) and HQIC (10.2348)) are the most suitable models for forecasting future predictions in ASPI and SL20, respectively. As a next step, up coming week values were forecasted using four different types of grey operational models, namely, GM(1, 1), GM(2, 1), grey Verhulst and new proposed NGBM.

Tables IV and V results show the measures of corresponding forecasting errors with respect to the five different models. These results clearly suggested that, grey prediction models generate small forecasting errors than traditional time series approaches for the limited data forecasting. However, for the large sample of data under the normality assumptions, traditional time series methodologies are more suitable than grey methodologies; especially GM(1, 1) give some dramatically unsuccessful results than ARIMA in model pre-post stage.

Based on these results, we suggested that, NGBM model is better both in model building and *ex post* testing under the *s*-distributed data patterns. Furthermore, GM(1, 1) is useful only for the short-term predictions. The results are coincided with some previous research works which have done based on GM(1, 1) accuracy testing's (Wu and Chen, 2005; Bin and Sheng, 2010; Wang, 2002).

4. Conclusion and future work

The economic data forecasting under the limited data patterns have been created big challenge in the modern economy today. Miscellaneous types of studies have been carried out to in literature to find out the forecasting patterns under the areas in finance and investments. However, most of them are not full suitable for forecasting's under the modern economic conditions. As a result, based on long-term and short-term operational strategies, GSTs introduced by Deng Ju-long in 1982 under the three different criterions; they are, incidence analysis, clustering analysis and forecasting.

As a subset of this literature, very few studies have focused to find the short-term forecasting with limited sample observations (weekly, monthly or quietly) in CSE. Therefore, the first time of literature, this current study focuses to examine the forecasting models over the two quietly period for 2014 October 2014 to December 2014 and 2014 December to 2015 March. The model accurate results in MAPE evidenced that, (MAPE [NGBM] < MAPE [Grey-Verhulst] < MAPE[*GM*(2,1) < MAPE [GM(1, 1)]) NGBM is more significant and make higher performances in model fitting as well as forecasting under the *s*-distributed data patterns. Indeed, result suggested that (MAPE [Grey-Verhulst] > MAPE [GM(2, 1) > MAPE [GM(1, 1)]) GM(1, 1) and GM(2, 1) are more accurate only for short-term than long-term predictions which can be easily applicable for monotonous variety process. The current study is totally coincided with Yu *et al.* (2000), Li *et al.* (2011), Wang (2002) who have done research works based on miscellaneous type of real world applications relates to the China.

Because of the chaotic and non-stationary behavioural fluctuations, it could be better to use the improved grey methodologies using hybrid models based on neural

Table III.
ARMA/ARIMA model selection

		ASPI					SL20		
p/q	0	1	2	3	*p/q*	0	1	2	3
0		10.7989	10.8356	10.8675	0		10.254	10.2906	10.2172
		10.8357	10.9093	10.9780			10.3279	10.4011	10.2541
		10.8131	10.8641	10.9101			10.2827	10.3332	10.2314
1	10.8469	10.8552	10.8493	10.8524	1	10.2822	10.2744	10.2031	10.2205
	10.8840	10.9296	10.9608	11.0011		10.3194	10.3487	10.3147	10.3692
	10.8612	10.8838	10.8922	10.9096		10.2965	10.3029	10.2460	10.2777
2	10.8747	10.8012	10.8882	10.8083	2	10.2810	10.1917	10.2397	10.2548
	10.9497	10.9138	11.0382	10.9960		10.3561	10.3042	10.3898	10.4424
	10.9035	10.8444	10.9457	10.8803		10.3098	10.2348	10.2973	10.3267
3	10.9215	10.9079	10.8762	10.9128	3	10.3278	10.0514	10.1867	10.2283
	11.0351	11.0594	11.0656	11.1401		10.4415	10.2029	10.3761	10.4556
	10.9649	10.9658	10.9486	10.9997		10.3712	10.1093	10.2591	10.3152

Table IV. The model accuracy for 4th quarter 2014

Model accuracy	ASPI ARIMA	ASPI GM(1, 1)	ASPI GM(2, 1)	ASPI Verhulst	ASPI NGBM	Model accuracy	SL20 ARMA	SL20 GM(1, 1)	SL20 GM(2, 1)	SL20 Verhulst	SL20 NGBM
20 September 2014 to 15 December 2014											
MAPE	0.3247	1.4381	1.1219	0.7621	0.3112	MAPE	0.3093	0.8973	1.1253	0.6321	0.3212
MAD	18.7590	41.7801	31.6754	24.5641	13.321	MAD	11.3290	28.9083	39.8730	19.8943	29.7453
RMSE	24.7851	47.9830	36.8791	32.8970	19.893	RMSE	13.3271	36.9831	44.9843	25.7630	36.0025
16 December 2014 to 20 December 2014											
MAPE	0.3595	0.3219	0.1358	0.1147	0.0246	MAPE	0.3231	0.3182	0.2294	0.17976	0.08168
MAD	26.2264	23.5055	9.8953	8.3707	1.7983	MAD	11.1379	12.9840	9.36572	7.3386	3.3344
RMSE	31.897	34.9406	10.7853	9.7960	2.1003	RMSE	13.8066	14.2120	9.5146	7.55085	3.56220

Table V.
The model accuracy for 1st quarter 2015

Model accuracy	ARIMA	GM(1, 1)	ASPI GM(2, 1)	Verhulst	NGBM	Model accuracy	ARMA	GM(1, 1)	SL20 GM(2, 1)	Verhulst	NGBM
21 December 2014 to 15 March 2015											
MAPE	0.4591	1.2251	1.1321	0.8654	0.3946	MAPE	0.4231	1.1324	1.09821	0.6453	0.3987
MAD	20.7678	39.4955	31.8765	26.3707	18.798	MAD	17.4906	32.7634	28.7865	23.8641	16.7452
RMSE	31.8975	40.9406	36.7853	34.796	28.100	RMSE	28.9941	37.7679	32.8765	28.7642	22.6541
16 March 2014 to 20 March 2015											
MAPE	0.4779	0.1778	0.1463	0.0711	0.0286	MAPE	0.40349	0.3695	0.2262	0.1126	0.0291
MAD	17.9199	12.5391	10.3163	5.0168	2.0225	MAD	15.4896	14.8721	9.1050	4.5346	1.1772
RMSE	20.5941	13.4738	11.3965	5.7318	2.8532	RMSE	18.4618	15.1393	9.7318	5.2980	1.62548

network and GA in real world model fitting and forecasting's. Finally, we strongly believed that, current study makes significant contribution to policy makers as well as government to open up new direction to develop the CSE investments in Sri Lanka.

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